



**Employee Usage of Generative AI as Moderator of High Workload Effects on Emotional
Exhaustion and Extra-Role Performance**

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Abstract

This quantitative study investigates the role of generative AI in moderating the negative effects of high workload on both emotional exhaustion (EE) and contextual performance (measured with OCB). Workload is investigated as a form of job demand whilst AI represents a technological job resource in accordance with the Job Demands-Resources Model (Demerouti et al., 2014). Four hypotheses were formulated based on the mentioned theory, previous literature contradicting findings, and research gaps, especially concerning the depopulation of AI tools at work. In fact OCB was previously found to directly and indirectly be affected by workload (Kasekende et al., 2020; Kissi et al., 2019), while AI was found to increase exhaustion although it should logically and theoretically decrease it (Rožman et al., 2023; Xu et al., 2023). It was hypothesised that higher workload would significantly increase EE and reduce OCB via direct linear relationships. Furthermore, the AI usage moderation analysis should impact the relation negatively for EE and positively for OCB. A cross-sectional self-report study was conducted among 127 Dutch and English speaking office employees of various sectors. Results showed that only the first hypothesis concerning workload and EE was confirmed while all the others were insignificant and in the opposite directions as expected. Finally, limitations, suggestions for future research, practical and theoretical implications are discussed.

Keywords: Workload, Emotional Exhaustion, Organisational Citizenship Behaviour, Performance, Generative AI.

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Introduction

Nowadays, there are numerous negative outcomes for employees due to nonoptimal job characteristics such as low organisational culture, stressful work environments, lack of trust among staff, and lack of autonomy and support of superiors (Bauer et al., 2014). Therefore, for jobs focusing on quantity and productivity which ulteriorly strain staff members, the possibility of automating redundant or superficial tasks may result in a significantly reduced physiological and psychological burden (Lee et al., 2018). Coping mechanisms are cognitive and behavioural strategies individuals can use to manage stressful demands and mitigate negative emotions (APA Dictionary of Psychology, 2024). These mechanisms can be conscious efforts (*i.e.*, problem-solving) or unconscious adjustments. The current outbreak of AI tools among office jobs' workforce, epitomised by ChatGPT, presents a new potential coping mechanism to help decrease performance pressures specifically for office workforce (Brynjolfsson & Raymond, 2023). Office jobs are typically administrative occupations involving tasks such as preparing and organising documents, tracking products, and providing information to the public (Giuliano, 1982). The work environment is structured with regular hours and repetitive computer tasks. These roles require skills in communication, organisation, and computer literacy.

AI could be considered a functional coping mechanism for job positions in which such tools create an adaptive strategy to help individuals manage challenging situations and maintain well-being (Algorani & Gupta, 2023). Integrative AI, is defined by the incorporation of artificial intelligence into existing systems, processes, or tasks to enhance functionality (Boucher, 2020). A sub-aspect of integrative AI is generative AI, which refers to a class of artificial intelligence capable of generating new content on request, such as text, images, audio, and codes (Brynjolfsson & Raymond, 2023). Thus, the combination of integrative and generative tools can have a great impact in the work environment to enhance processes by

generating immediate responses. For example, ChatGPT can produce coherent responses based on the input it receives (Brynjolfsson & Raymond, 2023). This technology has many potential applications and is becoming widely used due to its Q&A structure. Anyone can formulate questions on virtually any topic, providing opportunities for task modification, enhancement of knowledge, and a strong decrease in the time needed to retrieve information (Russell & Norvig, 2010).

In opposition to AI being a new concept within coping mechanisms in the workplace, job crafting is a widely studied form of positive individual's job modification. This refers to a proactive approach involving employees redesigning roles to better fit their objectives and strengths (Demerouti, 2014). In literature, it has been proven as a beneficial tactic ameliorating employee performance, engagement, and well-being (Moreira et al., 2022; Slemp et al., 2015). Crafting one's job can involve changing the tasks (task crafting), the relationships (relationship crafting), and the perceptions (cognitive crafting) according to one's work characteristics and personal preferences (Demerouti et al., 2019). Generative AI usage can thus theoretically be considered a new technological form of task crafting if seen as a proactive way of modifying or simplifying task requirements. In fact, it offers various task-focused means of dealing with workload, defined as the amount of responsibilities and projects undertaken in a specific time period (Johannsen, 1979). Since workload can be measured in terms of quantity, complexity, time and effort required to complete assignments (Johannsen, 1979); the help furnished by AI can make a concrete difference for employees. These tools help automate tasks and reduce the load from simple spell checks, email redaction, presentation designs and structures, to even writing entire reports.

As explained, task crafting is used to mitigate the adverse effects of high workload positions, characterised by excessive responsibilities and insufficient resources to fulfil them,

leading to strain (Rudolph et al., 2017). Emotional Exhaustion (EE) is a common form of strain and known antecedent of burnout, defined as extreme weariness and depletion brought on by extended exposure to demands (Liu et al., 2020). The association between workload and exhaustion is especially true in today's high stakes work environment, explaining the positive direct correlations repeatedly found in literature (Balducci et al., 2021; Bergeron et al., 2013; Bolino et al., 2015).

Compared to the wide research concerning workload and EE both independently and together, there appears to be a lack of investigations relating these variables to AI usage. The few available results show that technology frustration and AI awareness increase negative outcomes such as strain and depression (Tawfik et al., 2021; Xu et al., 2023). These findings contradict the idea that technology, specifically AI, simplifies work tasks and generates positive outcomes for employees. There is a significant research gap in understanding the interplay between AI usage, high workload, and EE. Theoretically, further investigations are needed to explore how this new form of job crafting alleviates and/or enhances job strain. The results can depend on user training, AI integration quality, and task complexity (Tarafdar et al., 2019). Practically, studies should focus on designing AI interventions that promote employee well-being, reduce EE, and improve job satisfaction. Then, research may help organisations to implement such interventions and optimise AI whilst controlling for the added stress of technology usage (Tarafdar et al., 2019; Venkatesh et al., 2021).

Similarly to the effects of workload on EE, having an excessive amount of work could logically be associated with a reduction of extra-role performance, also called contextual performance or commonly organisational citizenship behaviour (OCB). This performance measure is defined by voluntary actions going beyond the requirements of a formal job and addressed to benefit specific parties (Lavelle, 2010). In fact, literature separates OCBI and OCBO as behaviours directed at Individuals or at Organisations (Organi, 1988). OCBI

involves helping colleagues, providing emotional support, and assisting with work-related issues and mentoring. OCBO includes advocating for one's firm or suggesting improvements. Surprisingly, literature has found contradicting opinions on the negative effects of workload on OCB. It was found both that there is (Kissi et al., 2019) and that there is not a direct relationship (Bruggen, 2015), also, that this relation depends on explanatory variables such as perceived organisational support (Chen et al., 2009) and work autonomy (Msuya & Kumar, 2022). Such dispersed results generate an important research gap. Beyond empirical findings, contextual performance is linked to socially favourable workplace outcomes which may contribute to the contradicting results. In fact, OCB leads to promotions and praises by leaders, pushing workers to engage in it regardless of strain (Pradhan & Bhattacharyya, 2018). Nonetheless, it is also found that in case of extreme exhaustion or active burnout, employees do not prioritise engaging in extra-role tasks (Kasekende et al., 2020).

Regarding the role of AI in this relationship, there is again a strong lack of empirical studies investigating its effects on performance. Specifically, research is needed to examine how AI systems influence OCBI and OCBO in high-workload contexts. Investigating this is crucial for theoretical advancements, as it can provide insights into a new crafting method shaping workplace interpersonal and productivity dynamics. Practically, understanding these relationships can help organisations design AI implementations that foster positive outcomes at work, like enhancing productivity by optimising in-role and extra-role performance (Pradhan & Bhattacharyya, 2018; Kasekende et al., 2020).

Many contradictions revolve around the explained relationships above. Not only are there research gaps regarding AI tools' effects on EE and OCB research, but the literature in relation to generative AI and workload also presents conflicting findings. This study attempts to shed some light on these gaps by clarifying whether it is possible to find a supportive result of AI as a coping mechanism reducing EE, and increasing OCB. Lastly, finding a satisfactory

relationship between workload and contextual performance without the intervention of additional variables will be attempted.

The presented negative consequences associated with high workload lead to the research question: *"What is the impact of generative AI's moderation effect on the relationship of high workload with emotional exhaustion and with employees' contextual performance?"*. Knowing how AI can theoretically be a coping mechanism for staff due to its challenge-reducing nature, it becomes relevant to learn more on the human-computer interaction to see how this phenomenon is evolving with the advancing of technology in the workplace. This will contribute to the body of academic literature on AI and its application to social sciences topics such as HR. It is also scientifically relevant as the research will attempt to statistically confirm existing relationships and explore the rather new moderation effect of generative AI usage. This research also adds knowledge on psychological factors such as job-associated stress by proving that technology can reduce the consequences of heavy workload.

The practical implications of this study are significant for organisations. By demonstrating how generative AI can mitigate the adverse effects of workload on the chosen outcomes, companies can make informed decisions about supporting technologies. This could enhance employee satisfaction and productivity and reduce turnover (Tambe et al., 2019). Additionally, understanding the role of AI in boosting OCB and reducing EE can help organisations design better training programs to effectively use such tools, promoting a resilient work environment (Tarafdar et al., 2019). Implementing AI as a strategic tool to manage workload can also provide a competitive advantage by boosting innovation (Venkatesh et al., 2021).

Theory

Based on available theories providing a well-investigated overview of how job characteristics affect outcomes at work, the selected framework to theoretically position this paper in social sciences research is the Job Demand-Resource Model (JD-R). This is an established organisational psychology theory created by Demerouti et al. (2001). The JD-R Model helps comprehend the interactions among job demands, job resources, performance, and employee well-being outcomes. Thus, it is widely used in organisational literature to individually investigate demands and resources plus imply conclusions on their effects on each other.

This model can sustain the presented investigation of if and how jobs characterised by high work demands affect emotional exhaustion and extra-role performance outcomes (Albrecht, 2012). Additionally, if considering AI usage as a coping mechanism counteracting the demands-induced strain, the JD-R framework supports the interpretation of technology tools as job resources moderating the impact of demands and consequences. Within this model, demands are the aspects of the job that come with physiological and psychological costs and call for prolonged physical or mental effort, such as workload (Demerouti et al., 2001). Resources, on the other hand, are behaviours or tools on the job linked to higher motivation, engagement, and efficient functioning and may lessen the impact of high demands, such as generative AI (Demerouti et al., 2001). According to the model, employee outcomes are influenced by the balance between demands and resources; an unbalanced amount of demands can result in burnout and decreased performance, while a positive balance can improve individual's engagement and have a positive impact on organisational outcomes (Demerouti et al., 2001).

Thus, the JD-R Model can theoretically support the hypothesis of a positive direct correlation between high workload and emotional exhaustion. Employees are under more

pressure as their workload grows, which can exhaust their psychological reserves and cause EE, characterised by a depletion of reserves and feelings of tiredness, irritation, and cynicism regarding one's work (Balducci et al., 2021). Based on the JD-R Model, understanding and managing workload is fundamental to prevent EE and preserve well-being (Lee & Eissenstat, 2018). Other than theoretically, empirical evidence was also found for the increase in exhaustion levels as workload increases (Greenglass et al., 2003; Bruck et al., 2020). Additionally, DiStaso and Shoss (2020) found that anticipating changes in workload increase intensified the current workload–emotional strain relationship. This suggests that employees can get exhausted already by anticipating the feeling of strain due to higher demands. Positive results were also found with moderating variables like gender in this direct relation. Puranova and Muros (2010) examined gender influences in the relationship workload-EE, considering job control and social support as mediators. Women reported higher exhaustion under similar workload conditions, and differences in perceived job control and social support partially mediated this effect. Thus the first hypothesis of this study is formulated.

H1: High workload increases emotional exhaustion of employees.

A generative AI tool, such as ChatGPT, can be placed as a job resource within the JD-R Model because when used as task crafting, it could become an adaptive strategy for staff (Ritz et al., 2024). Adaptive strategies are behaviours used to mitigate the negative impact of heavy workload in one's personal life (Petrou et al., 2015). Generative AI should prove helpful for one to proactively change tasks to suit work needs (Ritz et al., 2024). By utilising tools like ChatGPT for task crafting, employees may streamline tasks, automate repetitive processes, helping experience a reduction in the emotional toll associated with work (Demerouti, 2014). This supports the core tenet of the JD-R Model, stating that resources can mitigate the negative effects of demands (Petrou et al., 2015). It also provides a fresh viewpoint on how emerging technologies could theoretically be incorporated into everyday

work practices. Reim and colleagues (2020) found that successful AI integration can enhance efficiency, decision-making, and innovation in business models, thus improving organisational performance. The study emphasises four key steps to reach such outcomes: understanding AI and necessary organisational capabilities, assessing current business models and potential for innovation, developing the skills for AI implementation, and achieving organisational acceptance. Furthermore, Rožman and colleagues (2023) investigated how AI can reduce employee's workload in a volatile, uncertain, complex, and ambiguous (VUCA) business landscape. They found that AI-supported organisational culture, leadership, and employee training influences employees' perceived workload reduction by AI. This enhances employee engagement which boosts company performance.

To better comprehend AI's multifaceted role in the workplace, a distinction can be made between its help in automating and augmenting demands. Augmenting demands emphasises using AI to improve problem-solving more than automating demands, which concentrates on simplifying repetitive tasks and decreasing workload (Fong, 2024). An employee might, for instance, use generative AI to automate repetitive tasks and reduce the associated burden (automating demands). Or, use AI to improve work capabilities by requesting feedback on complex tasks, resulting in more creative outputs (augmenting demands). Upon identifying these distinct usage categories, it is apparent that the implementation of generative AI tools can have a variety of scopes for individuals, ultimately also benefiting organisations by cultivating a dynamic workplace. In fact, workers who incorporate such tools into their work processes to simplify tasks might feel less perceived demands and consequently less drain from those who do not use this technology (Liu et al., 2020). Nonetheless, empirical results also contradict theoretical and literature affirmations. Tawfik and colleagues (2021) found that, in healthcare, frequent frustration with technology increases levels of exhaustion. Thus, it may be necessary to improve the integration of

technological tools and teach how to employ them before AI can become a positive easy-to-use instrument. Similarly, Xu and colleagues (2023) suggest that being aware of the impacts of AI tools, increases exhaustion which increases depression. Regardless of discrepancies, from the mentioned concepts arises the second hypothesis.

H2: The positive relationship between workload and emotional exhaustion is moderated by the usage of AI tools such that when the usage of these instruments is higher, the relationship is weaker.

Similarly to H1 above, the JD-R Model can also be used as theoretical evidence justifying the relationship of high workload leading to reduced performance. In fact, according to the theory, the strain imposed by high demands generates negative outcomes for people if sufficient resources are in place at the organisational level (*i.e.*, supervisors check-ups) or individual level (*i.e.*, task crafting) (Bauer et al., 2014). Today, in addition to duties that are specifically listed, extra attitudes like supporting company policies, assisting coworkers, and acquainting with recently hired staff are expected of everyone rather than being appreciated when present (Pradhan et al., 2012). Attitudes can be directed towards other individuals or for organisations benefits (Organi, 1988). These non-official behaviours are in literature identified by extra-role, contextual performance or OCB (Borman and Motowidlo, 1993). With minor variations in definitions, these constructs can be applied interchangeably as they all represent a person's will to act beyond official job requests (Pradhan & Bhattacharyya, 2018). Previous studies already hypothesised that a high workload negatively impacts extra-role performance, given that employees may prioritise mandatory tasks already being straining rather than taking on responsibilities (Kasekende et al., 2020). Nonetheless, publications have highly contradictory results. Some investigations provide inconclusive evidence of a direct relationship (Kasekende et al., 2020), some added sub-categories of extra-role performance to find a connection (Kissi et al., 2019), and others only found indirect

relationships mediated by several variables (Kumar et al., 2021). To stay in line with the JD-R model's theoretical implication, this study's hypothesis assumes a direct negative relationship. In fact, according to the theory, heavy work demands, should exhaust employees' resources and thereby impede their ability to engage in discretionary behaviours as an attempt to gain time to recover (Kissi et al., 2019; Kumar et al., 2021).

H3: High workload decreases extra-role performance of employees.

Lastly, following the same reasoning of H2, using generative AI as a job resource suggests that a moderation analysis could alter the relationship of H3, allowing employees to engage in extra-role activities despite high workload. This is also rooted in the JD-R Model's principle that appropriate resources can counterbalance the negative impact of demands (Petrou et al., 2015). Nonetheless, integrating AI into the workplace can present both challenges and opportunities for OCB (Jayaraman et al., 2024). These advancements may reshape traditional extra-role practices by offering new ways for employees to contribute positively to their organisations. However, adapting and learning to use AI tools would become formal requirements if they were integrated in organisations for employees to use them actively. Thus, a revision of the OCB definition would be necessary in the context of AI-driven work (Jayaraman et al., 2024). The hypothesis is that the extent of AI usage moderates the negative effects of high workload on contextual performance, allowing employees to engage more readily in discretionary activities contributing to productivity (Lavelle, 2010).

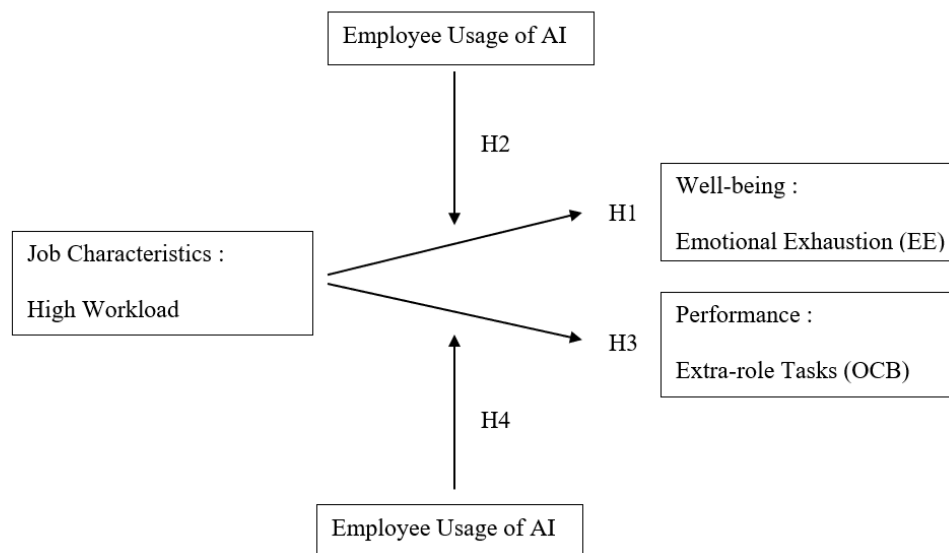
H4: The negative relationship between workload and extra-role performance is moderated by the usage of AI tools such that when the usage of these instruments is higher, the relationship increases.

In conclusion, the JD-R Model applied to the present study on generative AI offers a full understanding of the dynamics employees face in intensive jobs and proposes an

innovative spin on the resources part of this widely studied theory. As illustrated in Figure 1, by investigating the moderating role of an incredibly resourceful tool such as AI and its association with adverse job demands, EE, and OCB, this study aspires to contribute valuable insights to the body of literature informing new organisational strategies moving towards the integration of technologies. The JD-R Model emphasises the importance of balancing demands and resources and provides a simple yet robust foundation supporting the selected assumptions, exploring the complex interplay of the multiple factors affecting real-life work processes. The theoretical perspective adopted and its usage in this research underscores the potential of generative AI and maybe of integrative AI overall in reshaping the dynamics between job demands, resources, and employee outcomes (Brynjolfsson et al., 2019).

Figure 1.

Overview of the Hypotheses.



Methods

Research Design

This study is a quantitative survey research aiming to investigate the impact of the emerging role of generative AI tools on employees. The research is conducted cross-sectionally via a 10 minutes online questionnaire that participants only took once. This study is a component of a broader investigation on employee usage of generative AI at work. Five students worked together to collect the data. The questionnaire was available in both English and Dutch and received approval by the Ethics Review Board of the associated university before being administered.

Sample

A purposive sampling method was applied to select workers of any sector as long as their role was self-classified as an office job. This was to ensure that the sample could easily use generative AI at work for their daily activities via their computers. Inclusion required a slight pre-selection by asking people to consider whether they have at least a modest perceived experience in using generative AI at work, no minimum working hours but no less than one day of work per week, anyone above 18, any gender and any sector or type of firm. In opposition, underage people, students and manual workers (such as blue collar workers) were not reached out during the recruitment process or excluded later on as they could not grant a substantial generative AI usage in their work. To ensure that respondents sufficiently mastered the language to understand all the items, the two languages were already specified in the recruitment phase to make participants aware of this constraint and decide if they felt comfortable in using one of the two.

The conducted power analysis showed that 126 participants were necessary to reach what is considered a strong statistical power. After cleaning the initial dataset of 170 responses, 127 participants were counted, of which 53% specified being male and 46% female; almost half of the sample (46%) completed a “University Master or above”. 71 respondents (56%) chose the English survey version whilst 56 (44%) answered in Dutch. The average age for this sample is rounded without decimals to 34 years old ($SD = 12.78$), the average working hours per week are also rounded to 34 ($SD = 12.40$). Lastly, on average, participants have worked for the same employer for 6 years ($SD = 7.21$).

Instruments

The first useful instrument included in the survey was a series of demographic questions such as age, gender, time in years spent at the current organisation (tenure) educational level, and number of hours worked per week. All variables were used both as percentages or means to identify the general trends of the population and then as control variables. This is because different groups could have had a different perception of workload, experienced strain, engagement in OCB and usage of generative AI. For instance, different age groups may have varied workload levels and amount of technology usage. Differences in tenure may also affect responses since people who have been in the company longer may know how to cope better with demands, get less exhausted or are more aware of the benefits of engaging in OCB (Chan & Mak, 2014).

The concepts explained in the theoretical model were each measured with a specific scale having more than three items to ensure construct validity and all facets of the variable being investigated. Firstly, the chosen workload scale was the Questionnaire on the Experience and Evaluation of Work presented by Veldhoven & Meijman (1994). The scale contained fourteen items originally in Dutch and translated to English measuring the

perceived level of workload (see Appendix A). The internal consistency found for this study's sample was strong ($\alpha=0.82$). The ratings were on a 4-point Likert scale including always (1), often (2), sometimes (3), never (4). The items were introduced by "To what extent do the following questions apply to you" and followed by, for example, "Do you have a lot of work to do?".

The emotional exhaustion variable was measured with the Maslach Burnout Inventory (MBI) subscale of Emotional Exhaustion (EE) (Maslach & Jackson, 1981; Amri et al., 2021). This subscale showed high reliability ($\alpha=0.89$). The subscale was composed of nine items rated by a 7-point Likert scale including: never (1), rarely, occasionally, sometimes, often, very often, always (7), items are presented in Appendix B. The items investigated the perceived tiredness of the participant by asking questions such as "I feel emotionally drained from my work".

Further, the extra-role performance was measured by the General Performance Scale of Williams and Anderson (1991), specifically with the items belonging to the sub-dimensions of OCBO and OCBI. These had to be adapted to fit self-reports instead of supervisor ratings as initially created for. The Cronbach's alpha found was $\alpha=0.71$, meaning a medium reliability. The scale contained fourteen items in total (refer to Appendix C), 7 for each sub-dimension, measured by a 5-point Likert scale ranging from 1: strongly disagree to 5: strongly agree. Three items of OCBO were originally negatively coded and later statistically re-coded into positive. The items measured the extent to which participants willingly engaged in cooperative behaviours at work benefitting other individuals (*i.e.*, colleagues) or the organisation by asking questions like "I conserve and protect organisational property".

Lastly, the generative AI usage measurement subscales relevant for the scope of this research were the "automating demands" seven items scale and the "augmenting demands"

nine items scale (Fong, 2024). The reliability of the scale was high at $\alpha=0.94$. Both of these are structured as 5-point Likert scales, the complete list of items can be requested via contacting the original author as the paper is not published yet. While one focused on how much employees use generative AI to automate tasks, the other focused on managing job demands by investigating the tasks considered interesting and fostering creativity. The higher the rankings, the more participants used AI tools as the scales went from never (1) to always (5). The items were introduced by “At work I proactively” and followed by, for example, “Use generative AI to automate repetitive tasks”.

Procedure

The collection of data happened entirely via online requests and networking advertisements of the Qualtrics XM questionnaire. Recruitment methods included mainly personal reaching out to acquaintances to ensure that enough time was spent on answering the survey fully. A unionised message for all five students collecting data together was spread on LinkedIn and WhatsApp group chats. The survey started with a page of consent information and the language choice. The form included the aim of the study, the expectations for participants, ethical implications (like anonymity explanations) and practical information (like the time needed for completion). Then, all the used scales were presented in order and anonymity was granted all along the study.

Analysis

Once all the raw material was collected, the data cleaning and analysis was performed via the statistical software IBM SPSS version 29. Firstly, all the non-complete and biased answers were deleted (*i.e.*, extreme, neutral, dissent and acquiescence bias). Then, the non-relevant measurements for this study were also cleared (*i.e.*, time taken to complete the

survey). For the analysis, new variables with the mean scores on the four measurement scales were computed, then the reliability of each scale was verified to determine if the survey had high internal consistency. An exploratory factor analysis (EFA) was performed to verify whether the scales could statistically be considered four different measures (Eigenvalue ≥ 1) and if every item correctly measured what was intended of them. If this was the case, it would be possible to conclude that the construct validity is sufficient and the survey items were understood by participants. Considering that all the scales chosen, except for the generative AI one, had already been widely used in previous research, high Cronbach's alphas were expected along with strong item loadings to the four main factors.

Then, to actually investigate the hypotheses 1 and 3, two linear regression analyses were performed. The regression coefficients (between -1 & 1) indicated the strength and direction of the relationship between variables, showing how the dependent variables, EE and OCB, changed for each unit increase of workload, also considering other controlled factors in the model. A strong and positive relation was expected for H1, meaning that high workload leads to high exhaustion; but strong and negative significance for H3 where more workload leads to less OCB. Lastly, to investigate H2 and H4, moderation analyses were performed to verify if and to what extent generative AI usage can influence the above mentioned direct relations. To perform this on the SPSS software, the extended macro PROCESS was necessary (Hayes, 2013). Along with these tests, the presence of all the moderator analysis assumptions were verified for this sample. The interpretation of all results was supported by significance tests (p-values) and visual representations below.

Results

Firstly, a power analysis was conducted via an external tool (ClinCalc-Sample Size Calculator) to identify the minimum required sample given the effect size (0.15), significance level (0.05), power (0.80) and number of predictors (6). The required sample to perform this study resulted in 126 participants.

Then, an exploratory factor analysis (EFA) was conducted to identify the underlying structure of the questionnaire items related to Workload, AI Usage, EE and OCB. Using SPSS, principal axis factoring with varimax rotation was performed on all 53 items. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was 0.76. Bartlett's test of sphericity was significant ($\chi^2 (1378) = 3926.91, p < .001$), confirming that the correlations between items were sufficiently large for EFA. The eigenvalues suggested a twelve-factor solution, although only a four-factor one was conceptualised and even after separating all subdimensions of the selected scales (qualitative and quantitative workload, EE, OCBI, OCBO, AI's automating and augmenting demands), seven factors should have appeared. Despite high to moderate reliability on each scale, the readers may not have been able to assign the scale to the intended measure. Many items across measures were formulated quite similarly, possibly leading to unclear loading patterns and low face validity.

The first four factors, which were intended to explain all the cumulative variance, only explained 45.4% of the total variance. The rotated matrix from the output was cleared of all correlations smaller than $r = .50$ to simplify the analysis. The first four intended factors included a total of 34 clustered items out of 53. After rotation, all AI Usage items loaded onto Factor 1 with high to moderate correlations. Factor 2 presented seven items out of nine belonging to EE all with coefficients higher than $r = .63$. Factor 3 included five strongly loaded Workload items and one OCBO sub dimension variable with a moderate coefficient ($r = .52$). Factor 4 included five items out of seven of the OCBI sub dimension (Williams and

Anderson; 1991). Lastly, all other factors, ranging from 5 to 12, included only a singular or few dispersed items of the various scales. Out of 53 survey items, only four did not correlate to any factor with a coefficient of minimum .50. Nonetheless, twelve items in particular appeared highly scattered and could not clearly be assigned to a predefined scale.

Descriptive Statistics

In Table 1 below, the means, standard deviations and correlations among the four used measurements and possible control variables of this study are presented. These give an overview of the strength and direction of the associations, allowing identification of patterns, but not inferring conclusions. The findings show that workload significantly correlated with EE ($r = .50, p < .05$) although not significantly to AI usage ($r = -.04, p = .80$) and OCB ($r = .02, p = .69$). This means that as workload increases, so does exhaustion, whilst AI usage and OCB do not have a clear relationship with this independent variable. Nonetheless, AI usage positively and significantly correlates to EE ($r = .20, p < .05$), showing surprisingly that more AI is associated with more exhaustion. Also unexpectedly, the relationship between AI and OCB is not significant but negative, thus, AI usage is associated with less OCB performance ($r = -.02, p = .87$). Lastly, EE does not significantly correlate to OCB but found a negative direction ($r = -.07, p = .43$). This shows that higher exhaustion aligns with decreased engagement in OCB.

Table 1.*Descriptive Statistics and Pearson's Correlations of all Variables.*

Variables	<i>M</i>	<i>SD</i>	1	2	3	4	5	6	7	8	9
1. Workload	2.72	0.63	-								
2. AI Usage	2.48	0.84	-.04	-							
3. Emotional Exhaustion	2.68	0.98	.50**	.20*	-						
4. OCB Performance	3.85	0.41	.02	-.02	-.07	-					
5. Age	33.61	12.78	.20*	-.34**	-.02	.05	-				
6. Gender	1.50	0.59	-.06	.20*	.19*	-.14	-.05	-			
7. Educational Level	5.17	0.98	.22*	-.15	.16	.08	.22*	-.01	-		
8. Working Hours per Week	33.94	12.40	.36**	-.14	.20*	.01	.39**	-.10	.23**	-	
9. Years Working for Current Employer	6.07	7.21	.28**	-.34**	-.02	.00	.76**	-.02	.20*	.27**	-

Note. *N* = 127**p* < .05. ***p* < .01

Min-max scores: workload (1-5), AI usage (1-5), emotional exhaustion (1-7), ocb (1-5), age (years), gender (1 = male, 2 = female), educational level (1-6), working hours (hours), years working (years)

Hypotheses Testing

Hypothesis 1 proposed a direct positive relationship between Workload and EE. The linear regression shows a significant, moderate, positive relation. The unstandardized coefficient $B = .78$ ($p < .001$) states that for every unit increase in the independent variable, the dependent variable also gets significantly higher by .78. This coefficient shows the importance of workload in explaining variations of EE in this model. The total variance of EE explained by workload is 25% ($r^2 = .25$). For the five control variables, only gender appeared significant ($B = .35$, $p < .05$). Thus, it is a confounding variable hinting for gender-specific responses to workload and EE. Both the direction and strength of this direct relation are significant, leaving the first hypothesis statistically supported.

Hypothesis 2 aimed to investigate whether moderating the Workload-EE relation with AI Usage could be a plausible addition to the moderate direct relationship found in H1. After conducting the analysis with all five control variables (gender, age, educational level, working hours, tenure) via the SPSS extension PROCESS (Hayes, 2013), the unstandardized coefficient of the interaction between workload and AI Usage appeared small, positive and insignificant ($B = .08$, $p = 0.57$). The effects of workload and AI and their interaction accounted for 33% of the variation in EE ($r^2 = .33$). Gender was again the only control affecting the relation between workload and AI usage ($B = .31$, $p = .02$). Results are presented in Table 2. Hypothesis 2 posited that AI usage would attenuate the negative impact of workload on EE, implying a negative coefficient for the interaction term. Thus, results show that neither the strength nor direction of the expected relationship were found, leaving this hypothesis unsupported.

Table 2.

Moderation Model of Workload, AI Usage and their interaction for EE.

Variables	<i>B</i>	<i>SE</i>	<i>t</i>	<i>p</i>	<i>95%CI</i>		<i>R</i> ²
					<i>LL</i>	<i>UL</i>	
Outcome variable: Emotional Exhaustion							
Model 2: F(8, 127) = 6.95							.33
1. Intercept	1.70	.51	3.37	.001	.70	2.71	
2. Age	.01	.01	1.07	.29	-.01	.02	
3. Gender	-.02	.02	-.90	.37	-.05	.02	
4. Educational Level	.31	.13	2.38	.02	.05	.56	
5. Working Hours per Week	-.00	.01	-.29	.77	-.02	.02	
6. Years Working for Current Employer	.09	.08	1.10	.27	-.07	.24	
7. Workload	.76	.14	5.62	.000	.49	1.03	
8. AI Usage	.16	.10	1.70	.09	-.03	.35	
9. Workload * AI Usage	.08	.14	0.58	.57	-.19	.35	

Note. The Workload and AI Usage variables were mean centered prior to analysis.

Hypothesis 3 assumed a negative direct relation between workload and OCB performance. No control variable resulted significantly affecting this linear regression. The high and significant unstandardized coefficient showed that for every unit increase in workload, the OCB behaviour also highly varied but in the opposite direction than expected as it increased ($B = 3.71, p < .001$). Additionally, only 4% of the difference in OCB depended on the level of workload ($r^2 = .04$). The unstandardized coefficient, although significant, was not in line with hypothesis 3 due to its direction, leaving it unsupported.

Lastly, hypothesis 4 was modelled after H2 to verify whether the relationship between workload and OCB performance was affected by usage of AI such that the initial negative direct relationship would become positive via this moderator. Results after controlling for the five variables, although none significant, are presented in Table 3. The matrix showed a weak, positive, non-significant model. The variance in OCB was also extremely low and confirmed the relation as almost non-existent ($r^2 = .04$). The interaction term ($B = -.003, p = 0.961$) was non-significant and again in the opposite direction as assumed since a positive interaction term was expected to indicate the moderating effect of AI usage on the relationship between workload and OCB. Hypothesis 4 consequently also remained discarded.

Table 3.*Moderation Model of Workload, AI Usage and their interaction for OCB.*

Variables	<i>B</i>	<i>SE</i>	<i>t</i>	<i>p</i>	<i>95%CI</i>		<i>R</i> ²
					<i>LL</i>	<i>UL</i>	
Outcome variable: OCB Performance							
Model 1: F(8,127) = .63							.04
1. Intercept	3.71	.26	14.50	.000	3.21	4.22	
2. Age	.01	.01	1.22	.23	-.00	.02	
3. Gender	-.10	.07	-.57	.12	-.23	.03	
4. Educational Level	.04	.04	.97	.34	-.04	.12	
5. Working Hours per Week	-.01	.01	-.87	.38	-.02	.01	
6. Years Working for Current Employer	-.00	.00	-.70	.48	-.01	.01	
7. Workload	.01	.07	.12	.91	-.13	.15	
8. AI Usage	.02	.05	.33	.74	-.08	.11	
9. Workload * AI Usage	-.00	.07	-.05	.96	-.14	.13	

Note. The Workload and AI Usage variables were mean centered prior to analysis.

Discussion

This study aimed to provide a nuanced understanding of the interplay between workload, EE, OCB, AI usage, and various demographic factors within the framework of the Job Demand-Resource (JD-R) model (Demerouti et al., 2001). Results showed, in line with previous research, a positive significant correlation for the direct relationship between workload and EE and for the role of gender as a confounding variable (Balducci et al., 2021; Puranova & Muros, 2010). Further, the two hypotheses concerning the moderation of AI for EE and OCB resulted non-significant and showed the opposite direction as expected with exhaustion increasing with AI usage and OCB decreasing. Although not fitting with this paper's hypotheses, the results of AI are in line with previous findings regarding technology usage hustles (Tawfik et al., 2021; Xu et al., 2023). Lastly, the attempt to clarify the doubts surrounding the direct relationship between workload and OCB failed as the hypothesis was discarded even after controlling for five variables: gender, age, tenure, working hours and educational level. Thus, only one out of four hypotheses was confirmed, raising questions about improvements needed to obtain the expected outcomes.

Hypothesis 1 aligns with the fundamental theoretical implication of the JD-R model stating that as more demands are in place, strain gets higher unless sufficient resources are provided (Demerouti et al., 2001). This finding adds to the body of research on this widely proven direct relationship and serves for organisations to understand the need of providing adequate resources, such as supervisors support and job autonomy, to mitigate the negative impacts of high job demands on employee well-being (Bruck et al., 2020).

Except for the first hypothesis, this study's results regarding the application of the JD-R model can be considered mixed. The nonsignificant findings of Hypothesis 2 suggest that generative AI tools do not help reduce strain. Nonetheless, considering the very recent depopulation of this topic in research and the JD-R model implications regarding resources,

with further refinements, AI could act, in the future, as a valuable resource in managing job demands (Cardon et al., 2023). More research on developing and integrating such tools in the workplace could help find the expected stress mitigation results. This highlights the need to explore further how these tools can serve as resources, aligning with the JD-R model (Demerouti et al., 2014). For this to happen, the burden of learning how to use these tools and technology's adverse effects on employees must be resolved first (Jayaraman et al., 2024; Xu et al., 2023). Thus, AI as a moderator between demands and negative work outcomes such as EE may be ahead of its time, considering the lack of research of these instruments at work. In fact, before investigating the effects on work outcomes, there should be a clear quantification of topics such as: how much AI affects one's work, how and why workers are using AI, how firms are implementing it and with which intentions. Understanding the adverse effects of AI integration is crucial to then develop more resourceful tools (Tarafdar et al., 2019). This study adds a critical perspective to discussions on AI in the workplace and emphasises the need for a nuanced approach to technology integration (Tams et al., 2020).

Gender is the only control variable playing a significant role in both the direct relationship and the moderation of AI usage for workload-EE. This suggests that men and women experience and respond to workload differently (Matud, 2004). Societal stereotypes and gender roles could influence stress perception and management. For instance, women might report higher emotional exhaustion due to additional societal expectations or caregiving roles outside of work, which can exacerbate stress responses (Schaufeli & Bakker, 2004). This result was in line with previous research researching gender as a moderator for the direct relationship (Puranova & Muros, 2010). Controlling for gender showed its role as a confounding variable and clarified the relationship of the main effect, enhancing the robustness and precision of findings (VanderWeele & Shpitser, 2013). Practically, this finding

suggests gender-sensitive interventions and support systems in the workplace to address these disparities.

Regarding hypothesis 3, the direct relationship between workload and OCB has been contentious in existing literature, with this study contributing to the contrasting findings (Kasekende et al., 2020; Kissi et al., 2019; Kumar et al., 2021). The unexpected positive result suggested that higher workload may not decrease OCB as believed. One explanation could be that employees perceive workload as a challenge rather than a hindrance, motivating them to engage in more extra-role behaviours. Another possible explanation is that employees with higher workloads may receive more recognition from supervisors, motivating them to perform beyond requirements (Grant & Ashford, 2008). None of the five control variables (gender, age, tenure, working hours, educational level) affected the relationship, implying a much more complex connection between workload and OCB, which future research should better investigate. Factors like perceived person-organisation fit and allocentrism were previously proven to better explain the interaction (Kasekende et al., 2020; Kumar et al., 2021). These nonsignificant findings contribute to the literature by underscoring the multifaceted nature of the workload-OCB relationship. Better understanding how employees respond to workload and focusing on individual perceptions is necessary both theoretically and practically (Grant & Ashford, 2008). Additionally, the lack of effect from the control variables points for future research to explore other mediators and moderators, such as job satisfaction, organisational culture, and individual personality traits (Kasekende et al., 2020). This study encourages a more nuanced approach to examining workload and OCB, paving the way for future targeted organisational interventions (Kumar et al., 2021).

Hypothesis 4, suggested that AI usage does not enhance the relationship between workload and OCB regardless of control variables. Similarly to hypothesis 2, this outcome might be due to the need for more effective integration of generative AI tools at work, as the

current usage might not be sufficient to increase its impact on performance outcomes (Jayaraman et al., 2024). Additionally, AI usage might not directly influence extra-role behaviours, as these are often driven by interpersonal dynamics, intrinsic motivation and organisational culture rather than technological tools (Gagné & Deci, 2005). This indicates that while technology can help task completion, it does not motivate employees to engage further, nor sufficiently impact the perception of workload so that one would decrease it to engage in OCB (Davenport & Ronanki, 2018). Thus, there is neither a main effect of AI on OCB nor a significant influence in the relationship workload-OCB. Better moderators for this analysis may be job satisfaction, employee engagement, and organisational commitment (Organ, 1988; Chen et al., 2009). In fact, they are deeply rooted in the psychological and cultural aspects of the work environment, making them more effective in promoting OCB despite high workloads. The hypothesis results were unexpected as previous literature suggested that tools enhancing efficiency and reducing workload could positively influence performance, aligning with the JD-R model's principles (Gagné & Deci, 2005).

Limitations

First, it is noteworthy that the survey relied on self-ratings and perceived experiences rather than potentially less biased measurements such as dyadic assessments or supervisors' ratings, particularly for performance (Podsakoff et al., 2003). Self-reporting can introduce various biases like social desirability, where respondents portray themselves more favourably, and recall bias, where participants may not remember past events well (Nederhof, 1985). These issues could affect the validity of the results, and skew the data towards subjective assessments. Additionally, the study's sample heterogeneity is a notable limitation (Andrade, 2020). It included both working students and older adults, and participants were not recruited from specific organisations or industries. While this approach aimed to represent the general

population, the distribution was not properly normal. This may have affected the size and generalizability of the results, especially since AI at work is a relatively new subject.

The exploratory factor analysis (EFA) faced significant challenges, with twelve items loading onto unexpected factors instead of the anticipated four: Workload, AI, OCB and EE. This discrepancy might be due to several reasons like survey design flaws, inadequate factor structures, or the non-normal distribution of the sample, which violates one of the assumptions of factor analysis (Tabachnick & Fidell, 2013). The reliability of the scales were sufficiently high, yet the EFA results needed to be more consistent, suggesting barriers with construct validity.

These limitations argue that the survey's methodology could be refined for more accurate and reliable results. Firstly, by conducting a pilot study to refine the survey items and ensure they capture the intended constructs. Pre-testing helps identify issues with questions, such as item wording ambiguity and relevance, before the main study (Tools4Dev, 2021). This study's performance items initially regarded supervisor ratings but were reformulated into self-ratings. Plus, the workload scale was unofficially translated from Dutch. These changes may have impacted the meaning of the items and reduced the ability to represent the constructs. Another methodology improvement would be increasing the sample size to ameliorate the findings' validity, reliability and generalizability and meet all the assumptions of factor analysis (Explorable, 2021).

Furthermore, these self-reports methodology limitations are somewhat visible from the means in Table 1. OCB had a notably higher average ($M = 3.85$, $SD = .41$) than other key variables. Conversely, the means for workload and EE were lower than anticipated although not extreme ($M = 2.72$, $SD = .63$, $M = 2.68$, $SD = .98$). These may be partly explained by the average working hours per week being less than the typical full-time 40 hours ($M = 33.94$, $SD = 12.40$), indicating that most participants were working part-time or under conditions

requiring fewer hours. The presented discrepancies may partially justify the discarded hypotheses, as the collected data may not have reflected the experiences of overworked employees. Additionally, the perceived workload was not necessarily high, leading to a similarly moderate level of EE ($M = 2.72$, $SD = .63$, $M = 2.68$, $SD = .98$). Examining these slightly off means, already suggest that the survey's self-reported measures either did not fully capture the work conditions, or the specific sample is not the correct target group for AI usage at work. Additionally, the lower levels of perceived workload may be due to proficiency in using AI to reduce the demands, biasing the results of the regression and moderation. Another explanation in line with the JD-R model could be that the resources in place in the sample's firms have helped mitigate perceived workload and exhaustion, explaining the lower means for these variables compared to OCB (Demerouti et al., 2001). This explanation is less likely considering that participants were not recruited from specific organisations or industries. Lastly, a different explanation for the found means could be that the high average OCB scores were due to response bias, with participants potentially inflating their self-ratings.

For the AI usage measurement, the introduction of these tools in the workplace posits a new variable to study in HR research (Cardon et al., 2023). In this study, AI usage had the lowest mean, highlighting its limited adoption. The result may be due to the difficulty in recruiting employees who consider themselves AI users, suggesting a skills gap or need for higher awareness of this tool. This variable showed a significant positive correlation with EE but insignificantly and negatively with OCB. This implies that while AI can enhance efficiency, it can also contribute to increased stress levels due to the demands of adapting to new technologies (Brynjolfsson & Syverson, 2019).

Future Research

Future research should first address the methodological limitations identified in this study: ensuring normality and refining survey items to improve construct validity. Other studies should focus on longitudinal and experimental designs better capturing workload and AI usage's effects on EE and OCB. Additionally, enhancing AI measures beyond generative tools, by identifying additional AI moderators of a different nature (*i.e.*, other forms of integrative AI) may help improve the results of the analysis on workload and outcome variables. This new investigation should be paired with the consideration of contextual factors like culture and individual differences to maximise the applicability of AI's benefits. While this study confirmed the hypothesis workload-EE and partially showed the complex relationship workload-OCB, more research is needed to understand AI's impact on these variables. To improve research on the OCB variable, additional moderators should be explored focusing on more intrinsic characteristics (Chen et al., 2009). Lastly, future research should also delve deeper into how gender moderates the relationship between workload and EE, by investigating potential gender differences in AI usage (Puranova & Muros, 2010).

Practical Implications

The study's implications are relevant to employers and HR workers who are developing the implementations of AI tools in their firms. Increasing workload without providing functioning resources to cope, will lead to higher levels of exhaustion. AI was proven to not be a sufficient coping mechanism when used independently by employees, but it could be beneficial if organisations reduce the technological issues associated with it (Xu et al., 2023). Generative AI tools should be integrated at the company level along with training on how to use them and instructions on the risks and benefits to promote AI awareness without negatively impacting employees (Tawfik, 2021). Additionally, if employers are introducing this AI resource to help completing mandatory tasks in hopes of increasing OCB,

they might not get the expected results as not sufficiently inherent (Gagné & Deci, 2005). Lastly, due to the gender differences in the perception of workload and strain, organisations should provide more support to women to achieve a sustainable work-life balance (Puranova & Muros, 2010).

Conclusion

In conclusion, to answer the research question *"What is the impact of generative AI's moderation effect on the relationship of high workload with emotional exhaustion and with employees' contextual performance?"*. This study contributes to understanding the impact of generative AI's moderation effect on the relationship between high workload and EE, as well as OCB. While the direct relationships between workload and EE and OCB were not moderated by AI usage, somewhat promising results suggest that AI tools could still impact these work outcomes if revised. The findings underscore the complexity of these relationships and the need for continued research in this area to inform organisational practices and improve employee well-being at work.

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Appendix

Appendix A

Items of the Workload Measurement Scale

1. Moet u erg snel werken? → Do you need to work very fast?
2. Heeft u te veel werk te doen? → Do you have a lot of work to do?
3. Moet u extra hard werken om iets af te krijgen? → Do you have to work extra hard to get something done?
4. Werkt u onder tijdsdruk? → Are you working under time pressure?
5. Moet u zich haasten? → Do you have to hurry?
6. Kunt u uw werk op uw gemak doen? → Can you do your work at ease? (R)
7. Heeft u te maken met een achterstand in uw werkzaamheden? → Are you experiencing a backlog at work?
8. Heeft u te weinig werk? → Do you have too little work? (R)
9. Heeft u problemen met het werktempo? → Do you have problems with your work pace?
10. Heeft u problemen met de werkdruk? → Do you have problems with work pressure?
11. Zou u het kalmer aan willen doen in uw werk? → Would you like to slow down in your work?
12. Vindt u uw werk ingewikkeld? → Do you find your work complicated?
13. Heeft u moeite met uw werk, omdat het in de loop der tijd steeds ingewikkelder is geworden? → Do you struggle with your work because it has become increasingly complicated over time?
14. Moet u werk doen dat te moeilijk voor u is? → Do you have to do work that is too difficult for you?

Appendix B

Items of the Emotional Exhaustion Scale (MBI, EE subscale)

1. I feel emotionally drained from my work.
2. I feel used up at the end of the workday.
3. I feel fatigued when I get up in the morning and have to face another day on the job.
4. Working with people all day is really a strain for me.
5. I feel burned out from my work.
6. I feel frustrated by my job.
7. I feel I'm working too hard on my job.
8. Working with people directly puts too much stress on me.
9. I feel like I'm at the end of my rope.

Appendix C

Items of the OCBI and OCBO Scale

OCBI:

1. I help others who have been absent
2. I help others who have heavy workloads
3. I assist my supervisor with his/her work (when not asked)
4. I take time to listen to co-workers' problems and worries.
5. I go out of my way to help new employees.
6. I take a personal interest in other employees.
7. I pass along information to coworkers

OCBO:

1. My attendance at work is above the norm.

2. I give advance notice when unable to come to work.
3. I take undeserved work brakes (R)
4. I spend a great deal of time with personal conversations (R).
5. I complain about insignificant things at work (R).
6. I conserve and protect organisational property.
7. I adhere to informal rules devised to maintain order.