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Impact of Artificial Intelligence Tool Usage on Employee Productivity and Work Efficiency: An Empirical Analysis

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Abstract
This study examines the impact of artificial intelligence (AI) tool usage on employee productivity and work efficiency, focusing on task automation, manual workload, error rates, and focus levels. The applied quantitative, cross-sectional research design was based on a secondary dataset, which was collected on Kaggle, comprising of 5,600 employee-level observations. Python was used to perform descriptive statistics and Pearson correlation and multiple linear regression to assess relationships between AI usage and productivity outcomes. The findings reveal that the use of AI tools largely automate a task and decreases the number of man hours (hours) compared to manual work thus substantiating how the tool is playing a good role in improving operational effectiveness. Nonetheless, the application of AI and automation only had a small yet significant positive impact on the error rates implying that there could be risks related to over-dependence on automated systems. Moreover, the use of AI did not imply a substantial effect on the concentration of the employees, with the hours of meetings becoming one of the factors that influenced the concentration in a negative way. To enhance cognitive performance and reduce mistakes, AI tools should be embraced by organizations but with a human supervision to enhance efficiency. This study provides empirical, employee-level evidence on the multidimensional effects of AI, contributing to a deeper understanding of human-AI collaboration in the workplace.

Keywords:

- Artificial Intelligence
- Employee Productivity
- Work Efficiency
- Task Automation
- Manual Work Reduction
- Error Rate
- Focus Hours
- AI Tools
- Workplace Performance
- Data-Driven Analysis

1. Introduction

Improved artificial intelligence (AI) technologies have dramatically changed the workplace environment in modern society and they have altered the way work is done, decisions are taken and the level of productivity is attained. Companies within any industry are starting to incorporate AI tools into their workflows to enhance their efficiency, ease the workload, and increase overall performance outcomes (Brynjolfsson & Mcafee, 2017; T. H. Davenport & Ronanki, 2018). With automated data processing to intelligent decision support systems, AI has become an important enabler of digital transformation in modern organizations (Jarrahi, 2018). Among the most noticeable uses of AI in the workplace is the use of AI-powered tools that can help the employee to carry out routine and complex tasks more effectively. Such systems are natural language processing systems, automated analytics platforms, and intelligent assistants all of them are aimed at amplifying human capabilities, rather than replacing them (Wilson & Daugherty, 2018). The AI tools can automatize the repetitive tasks, enabling the employees to concentrate on activities that are of high value, which increases their productivity and operational efficiency (Autor, 2015). Here, the implementation of AI is commonly linked with a decrease in the number of manual operations, increased speed, and more accurate work (Acemoglu & Restrepo, 2020). Despite these potential benefits, the influence of the application of AI tools on the productivity of employees on the individual level is a discussion point. Although some sources indicate the beneficial impacts of automation in efficiency, others have listed such unintended outcomes as more errors, dependence on technology, and decreased thinking (Raisch & Krakowski, 2021; Riley, 1997). In addition, there is little knowledge in regard to the relationship between the use of AI and cognitive performance, such as focus and attention. Some are convinced that AI will be able to enhance attention because cognition is shared and other people think that excessive automation will lead to less involvement and control over attention (Tarafdar et al., 2019). A main weakness of the current literature is the general emphasis on organizational or macro-level studies of AI adoption, typically focusing on firm performance or innovation or industry-level results (Brynjolfsson et al., 2021). Although such studies present some valuable information on the strategic implications of AI, they do not consider micro-level processes of AI tools affecting work patterns and efficiency of individual employees. At the employee-level analysis is critical to comprehending the real processes through which AI can lead to productivity since the advantages of AI eventually have manifested themselves in individual performance enhancements (T. Davenport et al., 2020). Moreover, the current study relies on conceptual models, case studies, or survey-based strategies, to a large extent, which may not be adequate to answer the quantitative relationship between AI use and performance performance outcomes. There is an increasing need to carry out empirical research, grounded in large-scale data, that will explore the effects of the application of AI tools on quantifiable variables, such as the automation of the tasks, the number of man-hours worked, the rate of errors, and the concentration levels, in particular (Raisch & Krakowski, 2021). Such kind of data-based approaches would be in a position to provide more robust and generalized data regarding the effectiveness of AI in the actual working settings. The other significant gap is that there is low degree of integration of the different dimensions of productivity to a single model of analysis. Previous studies are more inclined to examine individual outcomes or outputs that are efficiency or accuracy without considering their relationship to each other. Nevertheless, productivity is multidimensional in nature and it consists not only of the efficiency in completing tasks, but also of quality and cognitive involvement (Autor, 2015). These dimensions will also be necessary to understand the overall AI effect on the work of the employees. In response to these gaps, the present study adopts a quantitative and empirical approach to examine the impact of AI tool usage on employee productivity and work efficiency. The primary objective of this study is to investigate the extent to which AI tool usage affects key indicators of employee productivity and efficiency. Specifically, the study aims to (i) examine the relationship between AI usage and task automation, (ii) assess the impact of AI usage on manual work hours, (iii) evaluate the combined effect of AI usage and automation on error rates, and (iv) analyze their influence on employee focus. By undertaking such a multidimensional analysis, the research aims to offer a subtle insight into the advantages and shortcomings of AI implementation in the workplace. Addressing the research gaps identified, this study will add to the extant body of literature in a number of ways. First, it will give empirical evidence of micro-level impacts of AI tool use based on a large-scale data. Second, it combines several aspects of productivity into a single analytical concept. Third, it illuminates confusing and even opposing impacts of AI on productivity and cognitive performance. These contributions are especially applicable to the organizations that may want to make the most out of the AI tools and to the researchers, who can possibly gain insights into the emerging nature of the human-AI partnership.

2. Methodology

2.1 Research Design

The current study is a quantitative and cross-sectional study having a goal to investigate the effects of the use of artificial intelligence (AI) tool on the productivity of employees and work efficiency. It is an empirical study based on statistical models of relationships between AI use and key performance indicators at the individual level. It uses a secondary data-driven approach which provides the possibility to objectively measure variables and test hypothesis rigorously with the help of standard statistical tools.

2.2 Data Source

The report utilizes a secondary dataset that was acquired on Kaggle, namely the "AI Productivity Features Dataset", which comprises comprehensive data about the work patterns of employees, the use of AI tools, and performance-related metrics (Singh, 2026). The sample consists of 5,600 observations and incorporates several variables that reflect employee roles, levels of experience, the intensity of AI usage, automation of tasks, and a set of variables that measure several measures of efficiency. The dataset will provide a general overview of the dynamics within the workplace and help to analyze AI-driven productivity at the individual employee level.

2.3 Variables and Measurement

The study involves a set of independent, dependent and control variables to test the hypothesized relationships. The use of AI tools is the main independent variable and is the number of hours per week that employees use AI tools. Another important key explanatory variable that is added in extended models is task automation, which is expressed as the proportion of tasks that are automated. The various dependent variables represent employee productivity and work efficiency. Manual work hours per week are employed as an inverted measure of efficiency, which indicates the level to which work is still being labor-intensive. The quality aspect of performance is the percentage of error rate, and focus hours per day is a proxy measure of effective work engagement and productivity. A few control variables are incorporated in the analysis so as to address the possible confounding effects. These include the number of years of experience, the score of the task complexity and the number of hours of meeting per week. Also, categorical variables are included to adjust the difference between the job characteristics and work environments including job role and level of deadline pressure.

2.4 Data Preprocessing

The dataset underwent a set of preprocessing actions using Python before being analyzed. Numerical variables with missing values were treated with median imputation and mode imputation was used to preserve distributional properties in categorical variables. One-hot encoding converted categorical variables (like job role) into dummy variables so as to allow inclusion in regression models. The predictor of deadline pressure was transformed into ordinal numerical scale in order to represent growing degrees of pressure. The procedure of outlier detection and treatment was conducted through the interquartile range (IQR) technique in which the outliers were bound within acceptable values to reduce their effects on the outcome. This measure guaranteed vigor of the statistical approximations. Also, the consistency of the data and type changes were checked to guarantee the compatibility with the regression modeling methods.

2.5 Analytical Techniques

The study involves both the descriptive and inferential statistical approach to the study of the data. Mean, standard deviation and minimum/maximum values as the descriptive statistics were calculated to provide an overview of the data set and also to learn how the important variables are distributed. In order to determine the quality and orientation of connections between variables that relate to efficiency and AI usage, Pearson correlation analysis was conducted. The analysis provides some preliminaries about the potential association and assists in the later modelling. Multiple linear regression analysis was conducted using four different models to test the research hypotheses. The former judges the impact of the use of AI tools on task automation. The second model investigates the correlation between AI use and manual work hours. The third model will evaluate the overall effects of AI use and task automation on the rate of errors, whereas the fourth model will examine the effects of these factors on the number of focus hours per day. Each model has the control variables that are relevant in order to make sure that the relationship being estimated is not biased by the external factors. Coefficients, p-values as well as R-squared values are used to interpret the regression results in order to determine statistical significance and explanatory power.

2.6 Tools and Software

All statistical analysis and pre-processing of the data were done in Python. The major libraries used in the paper are Pandas and NumPy to manipulate data, Seaborn and Matplotlib to visualize it and Statsmodels to analyze the regression. Python allows achieving reproducibility, flexibility, and effective processing of large amounts of data, which is why it could be used in empirical research of this kind.

3. Results

3.1 Overview of Dataset and Preprocessing Outcomes

A secondary dataset of 5,600 employee-level observations in different job roles and experience levels that was sourced on Kaggle was used to conduct the analysis. The variables in the dataset were the use of artificial intelligence (AI) tools, automation of tasks, work efficiency indicators, and organizational variables. The data was preprocessed thoroughly before analysis. Preliminary examination showed that some of the values were missing under some of the chosen variables like job role, AI tool use, the level of deadline pressure, and task complexity score. This was done by taking care of these missing values in an organized manner through proper imputation methods to cover these missing values. After doing this, the data set no longer contained any missing values, thus allowing sound statistical analysis. Categorical variables such as job role, level of deadline pressure were coded as numerical and dummy variable in order to be used in regression modeling. Due to the transformation, the dataset doubled to have several derived variables and the final analytical dataset contains 106 features. This change made sure that all the pertinent qualitative attributes were implemented in the empirical models. In general, the preprocessing phase guaranteed the consistency of the data and removed biases that would have been caused by the absence of values and made the data ready to further statistical analyses.

3.2 Descriptive Statistics

Table 1 gives the descriptive statistics of the main variables to be employed in the research. The findings give a summary of the central tendency and dispersion of the indicators of AI use and work efficiency. The results show that employees devoted about 10.69 hours weekly to the use of AI tools, which implies the presence of the moderate stage of AI adoption among employees. The average automation of tasks was 28.81%, which indicated that a considerable amount of work activities was assisted with AI systems. Conversely, the number of hours per week of manual work was also relatively high, averaging 22.86 hours (which means that AI had not completely substituted the old work procedures). In terms of performance results, the mean error rate was quite low (2.18%), which indicates that there are good work accuracy levels among the employees. Furthermore, the average number of concentration hours per day was 4.64, with the employees noting moderate productivity and concentration in their working activities.
The control variables were also varied significantly. The average experience of the employees was 10.49 years, and the task complexity rated 5.51 out of 10. The average time spent in meetings was 7.19 hours per week, which means that there is a significant amount of time spent on joint activities. In general, descriptive statistics (Table 1) indicate that there is a significant difference in AI usage, automation, and efficiency results among employees, which is a good foundation to conduct further inferential analysis.

Table 1: Descriptive Statistics of Key Variables

Variable	Mean	Std. Dev.	Min	Max
AI Tool Usage (hrs/week)	10.694	6.110	0.00	28.25
Tasks Automated (%)	28.812	17.867	0.00	76.30
Manual Work Hours (hrs/week)	22.860	7.013	10.00	42.15
Error Rate (%)	2.177	1.508	0.01	6.67
Focus Hours (per day)	4.640	1.507	1.00	8.00
Experience (years)	10.485	5.756	1.00	20.00
Task Complexity Score	5.509	2.861	1.00	10.00
Meeting Hours (hrs/week)	7.194	4.780	1.00	18.35

3.3 Correlation Analysis

The Pearson correlation table shows the correlation between the variables of AI usage, task automation, and work efficiency (Table 2). The findings give preliminary information on the trend and magnitude of correlations before regression analysis.

Table 2: Pearson Correlation Matrix

Variables	AI Usage	Automation	Manual Work	Error Rate	Focus	Experience	Complexity	Meetings
AI Tool Usage	1.000	0.652	-0.433	0.154	0.114	0.008	0.008	-0.151
Tasks Automated	0.652	1.000	-0.366	0.147	0.083	-0.004	0.018	-0.064
Manual Work Hours	-0.433	-0.366	1.000	-0.061	-0.090	0.002	-0.001	0.155
Error Rate	0.154	0.147	-0.061	1.000	-0.003	-0.125	-0.004	0.002
Focus Hours	0.114	0.083	-0.090	-0.003	1.000	0.009	0.001	-0.466
Experience	0.008	-0.004	0.002	-0.125	0.009	1.000	0.010	0.010
Task Complexity	0.008	0.018	-0.001	-0.004	0.001	0.010	1.000	0.009
Meeting Hours	-0.151	-0.064	0.155	0.002	-0.466	0.010	0.009	1.000

The AI tool use and task automation had a strong positive relationship ($r = 0.652$), meaning that the more AI tools are used, the more automated tasks. This correlation is also backed up in Figure 1 where it can be seen that there is evident upward trend between these variables.

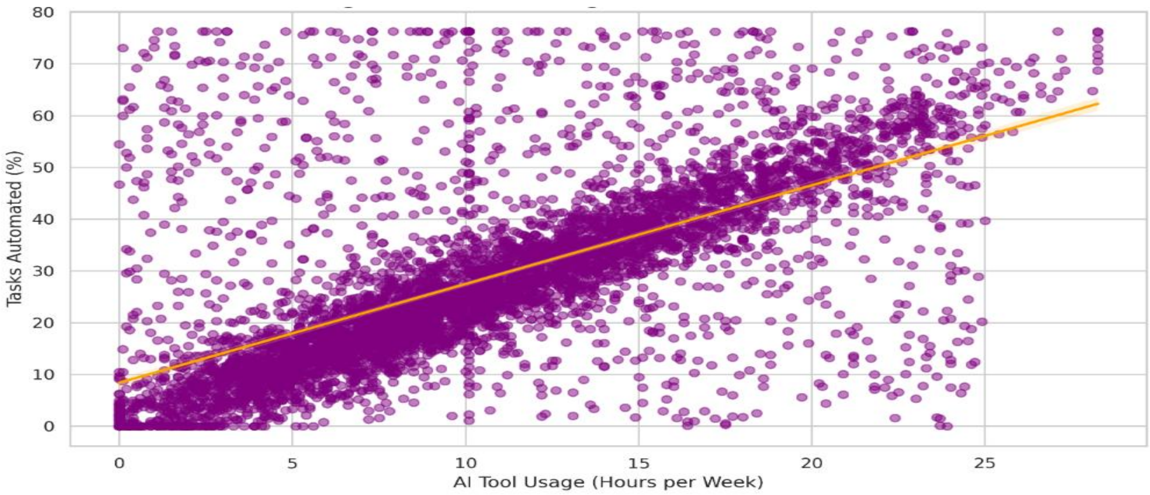

Figure 1. Relationship Between AI Tool Usage and Task Automation

Conversely, there was a moderate negative correlation between AI use and the number of hours working manually (r = -0.433), indicating that the higher the use of AI tools, the lesser the workload. Figure 2 also illustrates this negative correlation, indicating a decreasing trend between the use of AI and manual working hours.

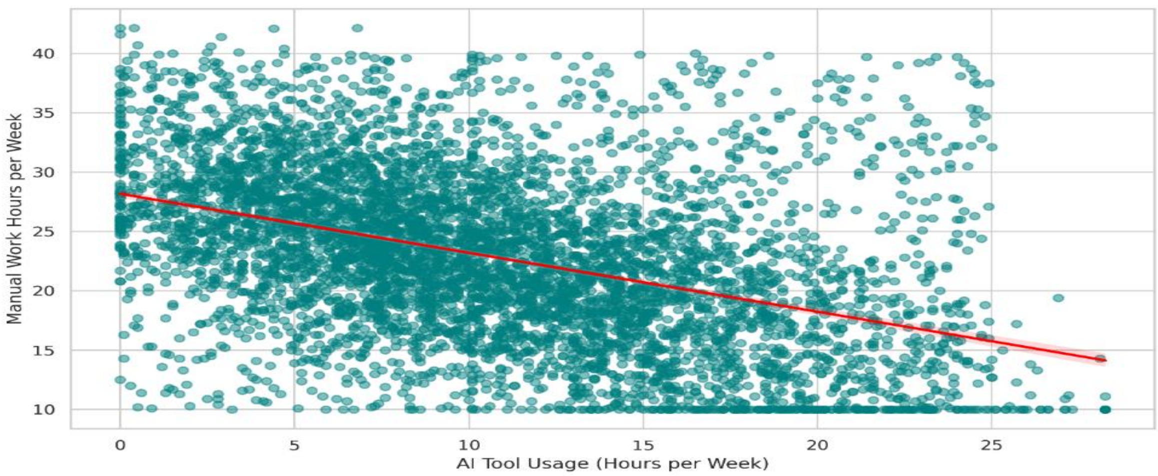

Figure 2. Relationship Between AI Tool Usage and Manual Work Hours

The correlation between the error rate and the use of AI was weakly positive (r = 0.154) which means that the more AI is used, the more the errors are likely to increase, but the strength of the relationship is rather weak. Likewise, AI use was weakly positively correlated with focus hours (r = 0.114), indicating a negligible increase in concentration of employees with increased AI use. The control variables showed a significant negative correlation between meeting hours and focus hours (r = -0.466), which implies that the amount of time spent in meetings can have a significant negative impact on the capacity of employees to remain focused in their work. The same trend can be observed in the heatmap of correlation (Figure 3) where the meeting hours and focus hours show a clear inverse relationship.

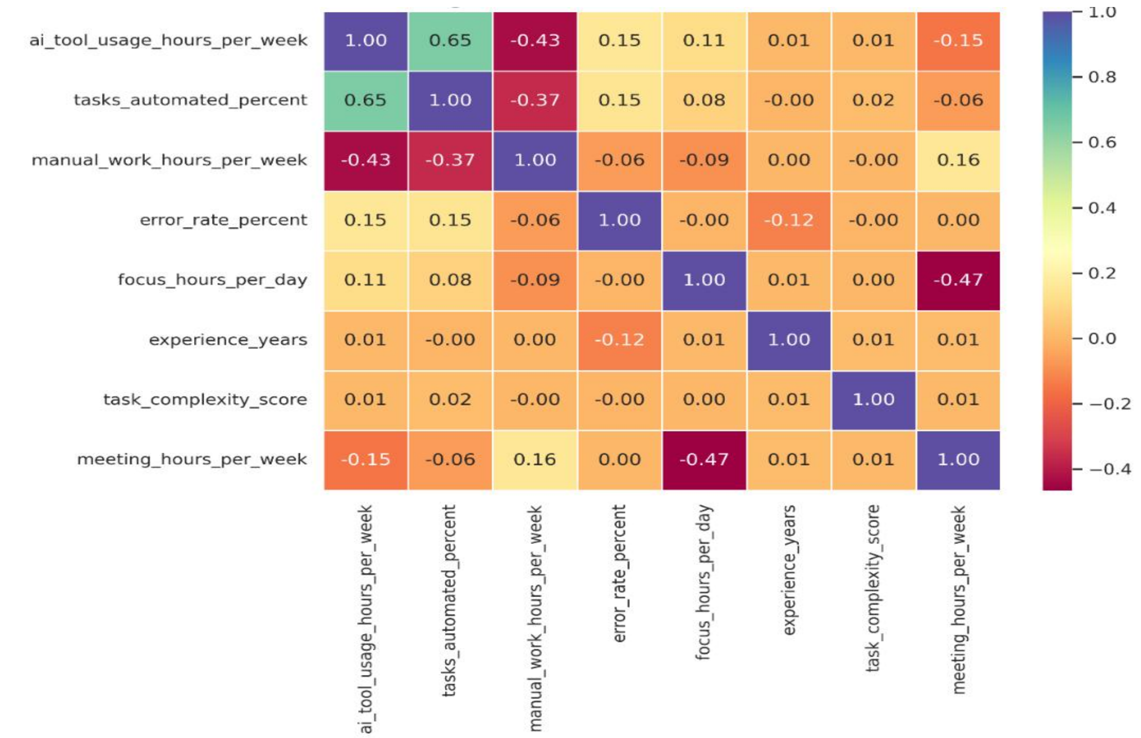

Figure 3. Correlation Heatmap of AI Usage, Productivity, and Work Efficiency Variables

On the whole, the results of the correlation (Table 2) indicate that AI adoption is highly associated with the higher level of automation and fewer manual labor, whereas the association with the rate of errors and attention is rather weak. These initial results give a basis to the further regression analysis.

3.4 Regression Analysis

In order to investigate how the use of artificial intelligence (AI) affects employee productivity outcomes, multiple linear regression models were estimated. Table 3 summarizes the results of these models and Table 3 contains detailed coefficients in the appropriate model tables. The results of the multiple regression models are summarized in Table 3.

Table 3: Regression Model Summary

Model	Description	R^2	Adjusted R^2	F-statistic	p-value
Model 1	AI Usage → Task Automation	0.567	0.560	83.04	0.000
Model 2	AI Usage → Manual Work Hours	0.270	0.259	23.50	0.000
Model 3	AI Usage + Automation → Error Rate	0.057	0.042	3.79	0.000
Model 4	AI Usage + Automation → Focus Hours	0.308	0.297	27.92	0.000

Model 1: AI Usage and Task Automation

Model 1 assesses the impact of AI tool use on the levels of automation of the tasks. The model exhibits good explanatory power with the R^2 of 0.567 (Table 3) implying that about 56.7% of the change in the automation of the tasks is being explained by the independent variables. The use of AI tools has a positive and statistically significant impact on automation of tasks ($\beta = 1.924$, $p < 0.001$), implying that more frequent use of AI tools will have a significant positive impact on the percentage of automated tasks (Table 4). This observation is in line with the visual tendency in Figure 1 where the more AI is used the greater the level of automation. Meeting hours per week are another control variable, which has a positive and significant relationship ($\beta = 0.234$, $p < 0.001$), which suggests that collaborative settings could support automation. Experience and task complexity on the other hand do not indicate statistically significant effects. Comprehensively, Model 1 shows that the adoption of AI is one of the driving factors of automating tasks in organizations.

Table 4: Regression Results (Model 1 - Task Automation)

Variable	Coefficient	Std. Error	t-value	p-value	Significance
Constant	10.652	4.454	2.392	0.017	**
AI Usage	1.924	0.034	57.104	0.000	***
Experience	-0.012	0.028	-0.446	0.656	ns
Task Complexity	0.085	0.056	1.519	0.129	ns
Meeting Hours	0.234	0.043	5.431	0.000	***

Note: ****p < 0.01, **p < 0.05, *p < 0.10, ns = not significant.*

Model 2: AI Usage and Manual Work Hours

Model 2 explores the correlation between the use of AI and the manual working hours. The model predicts 27.0% of the variation of manual work hours ($R^2 = 0.270$; Table 3). These findings reveal that there is a strong negative correlation between the use of AI and manual work hours ($\beta = -0.478$, $p = -0.001$). This indicates that the more the use of AI technology, the less time is wasted on manual activities (Table 5). Figure 2 shows this relationship as well with the number of hours spent at the workplace decreasing with the number of hours spent with AI. The number of hours per week of meetings positively and significantly influences the result ($\beta = -0.083$, $p < 0.001$), so more time spent on meetings can decrease the efficiency of AI realized by taking up valuable time. Other control factors, such as experience and complexity of the tasks do not show any significant effect. These results support the role of AI in the decrease of manual labor and enhancement of the operating efficiency.

Table 5: Regression Results (Model 2 - Manual Work Hours)

Variable	Coefficient	Std. Error	t-value	p-value	Significance
Constant	32.636	2.285	14.286	0.000	***
AI Usage	-0.478	0.017	-27.636	0.000	***
Experience	0.010	0.014	0.663	0.507	ns
Task Complexity	0.020	0.029	0.707	0.480	ns
Meeting Hours	0.083	0.022	3.745	0.000	***

Note: ****p < 0.01, **p < 0.05, *p < 0.10, ns = not significant.*

Model 3: AI Usage, Automation, and Error Rate

The Model 3 analyses the two components of AI use and task automation that influence the error rates by employees. This model has a relatively low explanatory power ($R^2 = 0.057$; Table 3), which implies that the proportion of variance in error rates explained by the included variables is also very small.Use of AI ($\beta = 0.027$, $p < 0.001$) and automation of tasks ($\beta = 0.006$, $p < 0.001$) are positively and statistically significant factors that relate to error rates (Table 6). It implies that despite the efficiency AI brought, there are some small increments in the error, which could be explained by over-dependence on automated systems or system constraints. Surprisingly, there is a large negative impact on employee experience ($\beta = -0.035$, $p < 0.001$), meaning that the more experienced employees are, the lower the number of errors they commit. Other variables, such as the complexity of tasks and the number of meetings, do not demonstrate significant effects. On the whole, Model 3 implies an efficiency-accuracy trade-off, which underlines the importance of integrating AI in a balanced manner.

Table 6: Regression Results (Model 3 - Error Rate)

Variable	Coefficient	Std. Error	t-value	p-value	Significance
Constant	1.868	0.571	3.272	0.001	***
AI Usage	0.027	0.006	4.940	0.000	***
Automation	0.006	0.002	3.501	0.000	***
Experience	-0.035	0.004	-9.923	0.000	***
Task Complexity	-0.003	0.007	-0.402	0.688	ns

Note: ****p < 0.01, **p < 0.05, *p < 0.10, ns = not significant.*

Model 4: AI Usage, Automation, and Focus Hours

Model 4 assesses how AI use and automation affect the number of hours employees are focused on. The model accounts about 30.8% of the variance in the focus hours ($R^2 = 0.308$; Table 3).

Surprisingly, the use of AI ($\beta = -0.001$, $p > 0.05$) and automation of the task ($\beta = 0.002$, $p > 0.05$) do not have statistically significant impacts on the focus hours (Table 7). This indicates that the use of AI has no direct effect on the capacity of workers to be focused when performing working tasks.

Table 7: Regression Results (Model 4 - Focus Hours)

Variable	Coefficient	Std. Error	t-value	p-value	Significance
Constant	5.024	0.474	10.596	0.000	***
AI Usage	-0.001	0.005	-0.153	0.879	ns
Automation	0.002	0.002	1.004	0.315	ns
Experience	0.003	0.003	1.015	0.310	ns
Meeting Hours	-0.135	0.005	-29.507	0.000	***

Note: ****p < 0.01, **p < 0.05, *p < 0.10, ns = not significant.*

However, meeting hours per week show a strong negative and statistically significant effect ($\beta = -0.135$, $p < 0.001$), indicating that increased meeting time substantially reduces employees' focus. Figure 4 is a clear indication of this relationship.

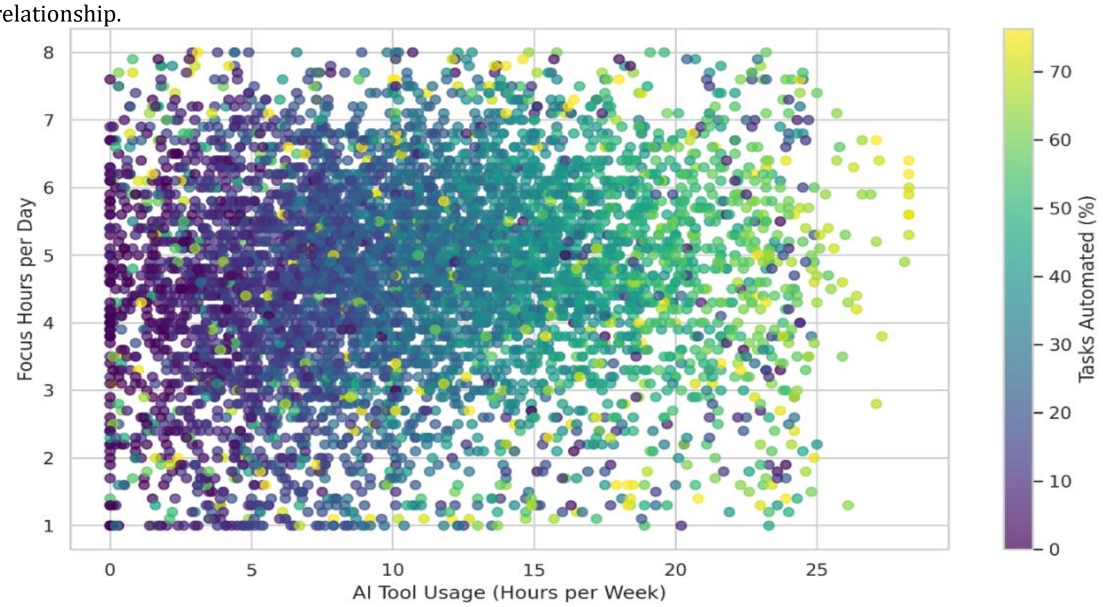

Figure 4. Combined Effect of AI Tool Usage and Task Automation on Focus Hours

These findings imply that organizational factors, particularly meeting load, play a more critical role in determining focus levels than AI usage itself.

3.5 Summary of Hypothesis Testing

The study hypotheses were tested according to the regression analysis results, as shown in Table 3, to identify the effect of AI tool use on the productivity and work efficiency of employees.The initial hypothesis, according to which the usage of AI tools positively influences the automation of tasks significantly, is well supported. As shown in Model 1, the positive relationship between AI usage and task automation ($p < 0.001$) is highly significant; it supports the hypothesis that greater the use of AI tools, the more work tasks are automatized.The second hypothesis according to which AI use saves the number of hours spent on manual work is also confirmed. Model 2 results provide the understanding that there is a significant negative correlation between the activities of employees who rely more on AI tools ($p < 0.001$), and thus, spend less time on manual work. The third hypothesis that AI use and automation lead to better accuracy in work through lowering the number of errors is not proven. In a surprising twist, the positive association between AI usage and automation and rates of error is statistically significant in at least one direction ($p < 0.001$). That implies the possibility of small inefficiencies or errors with the increased use of AI, or even some setbacks in the system or too much reliance on computer outputs. The fourth hypothesis, stating that the importance of AI use in improving employee focus is not proven either. Model 4 suggests that the level of AI use or automation of tasks does not impact focus hours statistically significant ($p > 0.05$). Rather, emphasis seems to be more contextually determined like meeting hours. Comprehensively, the hypothesis testing findings reveal that the use of AI can enhance operational efficiency because of its abilities in automation and decreased manual workload significantly. Nevertheless, it has minimal effects on cognitive performance like concentration and accuracy and in other instances, the opposite of the anticipated. 3.6 Insights from Visualizations The statistical results are also supported and complemented by the graphical analysis as it presents important relationships between the study variables. Figure 1 illustrates the correlation between the use of AI tools and automation of the tasks, which has a notable upward trend. This visualization supports the findings of the regression, which showed that more automation of tasks is linked to the higher levels of AI use. The figure 2 shows the correlation between AI utilization and the hours of manual work. There is a clear negative tendency, which proves that the more the workers interact with AI applications, the fewer hours they spend on the manual work. This graphical data is in line with the large negative correlation found in Model 2. The correlation heatmap (Figure 3) provides an in-depth view of the relationships between all the key variables. It is evident that strong positive correlations exist between the use of AI and automation of the tasks and negative correlations between the hours of manual work and automation. Also, the heatmap shows that the relationship between the meeting hours and focus hours is strong, negative, which means that the organization dynamics influences productivity. Figure 4 looks at the additive correlation between the use of AI, automation, and hours of focus. Compared to the above-mentioned numbers, there is no powerful and consistent trend that could be identified, which confirms the results of the regression that the use of AI does not have a significant impact on the level of employee attention. In general, the visualizations offer intuitive support to the statistical findings and prove that the adoption of AI mostly benefits efficiency-related outcomes, with little effect on cognitive performance scores, including focus.

4. Discussion

The results of the current study present valuable empirical data regarding the effects of the use of artificial intelligence (AI) tools on employee productivity and work efficiency. The research expands the available knowledge since, through a massive dataset of employees, the authors are able to analyze their efficiency outcomes, as well as their cognitive outcomes, in a single analytical context. The findings indicate that AI adoption is much more likely to increase operational efficiency (highly automatizing the number of tasks and decreasing the level of manual work) but its effect on the cognitive dimension (focus and accuracy) is more subtle and multidimensional. Among the most remarkable uncovers, one should outline a high positive correlation between the use of AI tools and automation of tasks. This finding aligns with the existing literature that emphasizes the use of AI to simplify the routine procedures and make employees focus on more worthwhile endeavors instead of repetitive ones (Bessen, 2018; Frey & Osborne, 2017). The high explanatory rate of the model also indicates that AI tools are quite useful as far as promoting automation at the individual level is concerned. This confirms the fact that AI can be used as a productivity-enhancing technology that can supplement human abilities, but not substitute labor (Cockburn et al., 2018). The use of AI tools also cut down on work hours done by humans greatly in addition to making work more automated. This observation is supported by the wider body of research on digital transformation, which focuses on benefits related to efficiency of automation technologies (Manyika et al., 2017). The AI tools will enable employees to dedicate more time to strategic and creative processes since they will spend less time on labor-intensive processes. This decrease in human labor can be viewed as a crucial aspect of work performance and highlights the effective utility of AI implementation in the organizational setting (Bughin et al., 2018). Nevertheless, the research also reveals a less obvious result in the correlation between the use of AI, the automation, and the level of errors. The findings on the topic are contrary to assumptions that automation improves accuracy because they suggest that there is a marginal yet significant rise in error rates that are linked to increasing AI usage and automation of tasks. The observation can be attributed to the notion of automation bias, whereby users become overly dependent on automated systems, and this is likely to cause them to ignore the mistakes made by the automated systems (Dzindolet et al., 2003). Moreover, AI-based tools can lead to the emergence of novel errors caused by the weaknesses of algorithms or using them in incorrect situations (Amershi et al., 2019). Such findings reveal the value of human control in the AI-supported processes to guarantee quality and reliability. The other important outcome is that there is no significant correlation between AI usage and employee focus. Although the hypothesis was that AI tools would help to focus more by decreasing the cognitive load, the findings indicate that the focus is not directly affected by the adoption of AI. Rather, the organizational factors especially the meeting hours were also found to negatively affect focus strongly. This observation is in line with previous studies which show that too many meetings may interfere with workflow and decrease the capacity of employees to do deep, focused work (Perlow, 2012). It implies that the idea of enhancing productivity will demand both technological and organizational interventions that will facilitate effective working practices. The collective understanding of these results indicates that AI does not have a strong impact on efficiency by changing its cognitive activity but by structural modifications in the execution of tasks. Although the advantages of automation and the decrease of the workload are obvious, the insufficient effect on attention and the possible number of mistakes suggest that the implementation of AI should be controlled. When utilizing AI tools, organizations must aim to find a balance between functionality and human expertise and prevent all the dangers of over-dependence on automation (Jussupow et al., 2024). Although it has its contributions, this study suffers a number of limitations. First, the analysis is done using cross-sectional data thus restricting the possibility of establishing time-dependent causal relationships. Longitudinal research would reveal more details about the changes in effects of the AI adoption as the employees become familiar with them. Second, the dataset lacks contextual factors like the organizational culture, type of industry, and technological infrastructure, which can modulate the success of AI implementation. Third, the paper is based on quantitative methods of productivity and fails to address qualitative factors like employee satisfaction, motivation, and perceived usefulness of AI tools. These are critical in appreciating the general ramifications of AI in the workplace. The other constraint has to do with measurement of error rates and focus that might not be fully reflective of complexity of cognitive performance. For example, focus hours may not necessarily reflect the quality of attention, and error rates may vary depending on task type. The further studies must address more sophisticated indicators of cognitive outcome, which may include behavioural or experimental statistics. Considering these shortcomings, some future research directions can be identified. To investigate how productive and efficient effects of AI adoption change over time, first, it is crucial to study longitudinal datasets and investigate how it changes. Second, it would be beneficial to incorporate the data available on the firm or industry level to get a more holistic view of how organizational factors affect AI outcomes. Third, it may be possible to examine the moderating effects of training and digital skills in the relationship between AI use and performance outcomes since the capability of employees to utilize AI tools properly is likely to moderate their effect (van Laar et al., 2020). Additionally, the interaction between AI tools and the human decision-making processes should be explored. Since AI systems continue to grow and enhance, it will be crucial to comprehend how employees perceive and respond to information generated by AI to make the most of its advantages (Shrestha et al., 2019). Finally, more studies are required to examine the ethical and psychological impacts of implementing AI, including the issues of trust, transparency, and job satisfaction. Overall, this study demonstrates the opportunities and difficulties of the AI implementation into the workplace. On the one hand, AI tools have less obvious impact on cognitive performance and accuracy than their efficiency because of the automation of work and reduction of manual workload. The findings have underscored the necessity of adopting a tempered nature when it comes to integrating AI that does not override the ability of technology without necessarily compromising human judgment and organizational support systems.

5. Conclusion

The research provides empirical data on the impact of the use of artificial intelligence (AI) tools on employee productivity and work efficiency that relies on a large-scale dataset, employee-level. The results indicate that the adoption of AI would be largely effective in improving operational efficiency through augmenting tasks automation and cutting-down manual work hours. These results confirm the idea that AI technology is an effective productivity facilitator; in other words, it streamlines workflow and minimizes repetitive efforts. However, the study also reveals that there are also serious problems regarding the implementation of AI. The outlined increase in the rate of errors suggests that overdependence on automated systems might lead to the emergence of undesirable inefficiencies and consequently the need to support AI technologies with human control and proper attention to the relevant factors. Also, the fact that the significant correlation between AI use and focus hours was not found indicates that organizational conditions and not technology use impact more significantly on the cognitive aspects of productivity i.e., meeting load. In general, the paper highlights the significance of putting AI implementation into a holistic framework wherein its benefits in technology are matched with effective practices in an organization. This study offers a multidimensional perspective on the relationship between AI and productivity performance, therefore, enriching the current knowledge of AI in the workplace. It is suggested that in the future, further optimization of technologies, along with human factors, can be adopted to bring the full potential of AI-based productivity enhancement to reality.

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