Market Dynamics Journal

RESEARCH PAPER

A Comparative Study of AI-Driven Efficiency and Motivation in Private and Public Work Environments

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Abstract: This study explores how AI language models impact workplace efficiency and employee motivation within varied organizational settings. Using statistical analyses and graphical visualization, it examines the relationships among Discussion Level, AI Usage Proportion, and Efficiency—quantified by the Annual Bonus Increase Ratio for private sector employees and the Oral Praise Increase Ratio for public sector workers. Findings reveal a positive link between AI usage and Efficiency in the private sector, where performance is largely driven by financial incentives. In the public sector, verbal praise from superiors is a primary motivator, with AI assistance particularly enhancing efficiency in politically sensitive contexts. Graphical analysis shows distinct Efficiency distribution patterns, highlighting unique preferences and constraints in AI utilization across organizational types. This research underscores the need for a nuanced understanding of AI adoption dynamics to optimize workflows and elevate employee performance.

Keywords: Comparative analysis, AI language model, Workplace efficiency, Employee motivation

1. Introduction

In recent years, significant progress has been made in natural language processing thanks to large language models [1-6]. These models, trained on extensive text data [7], excel in tasks such as generating text [8], answering questions [9], and other language-related activities with remarkable accuracy [10-13]. One notable advancement in this field is the adoption of transformer architectures and the associated attention mechanisms [14,15]. Transformers employ self-attention to assess the importance of different input segments, significantly improving the models' ability to handle long-range dependencies in natural language texts [16]. This mechanism enables a deeper understanding of word relationships within sentences, regardless of their positions.

These innovations have propelled language models forward, allowing them to comprehend and generate human-like text with a nuanced understanding of language structure and context. This not only reduces redundancy but also enhances overall performance, marking a significant leap in the field of natural language processing. Therefore, from this perspective, contemporary language models can not only contribute to the dissemination of knowledge but also provide assistance in copywriting for work [17-19].

Yuan et al. [20] evaluated Wordcraft through a user study, where participants wrote short stories with and without the tool. The results indicate that large language models enable novel co-writing experiences. For example, the language model can engage in open-ended dialogue about the story,

Received: Oct 05, 2024
Revised: Oct 30, 2024
Accepted: Nov 11, 2024
Published: Nov 16, 2024

respond to authors' custom requests expressed in natural language, and generate suggestions to overcome obstacles in the creative process. Building on these findings, further discussion is provided on the design implications for future human-AI co-writing systems. Lewis et al. [21] pointed out that the biomedical natural language processing (BioNLP) community has access to a large array of pretrained models. Finding the optimal model for a specific task can be difficult and time-consuming. In response to this challenge, they presented a large-scale study covering 18 established biomedical and clinical natural language processing tasks to assess the performance of several popular open-source biomedical and clinical NLP models under different settings.

Lee et al. [22] introduced CoAuthor, a dataset designed to reveal the capabilities of GPT-3 in creative and argumentative writing. CoAuthor captures rich interactions between 63 authors and four instances of GPT-3 across 1445 writing sessions. We demonstrate that CoAuthor can address questions regarding GPT-3's language, ideation, and collaborative abilities, and reveal its contribution as a writing "collaborator" under various definitions of effective collaboration. Kim et al. [23] proposed a method for designing anomaly-based host intrusion detection systems based on system call language modeling, which can learn the semantic meanings and interactions of each system call. Chen et al. [24] implemented a chemical language model consisting of a conditional transformer architecture for compound design, guided by observed potency differences. This model has demonstrated the ability to predict known potent compounds from different activity classes not encountered during training, thus confirming its capability to generate structurally diverse highly potent compounds.

To the best of our knowledge, research reports on large language models have so far assumed that users can access commonly used language models such as GPT. However, there has been no investigation into regions subject to international internet regulations. Additionally, within these regions, due to insufficient experience with GPT among evaluators, there may be varying abilities to evaluate the design copy assisted by language models for different types of tasks, leading to inconsistent recognition among employees. To address these issues, we conducted a study focusing on mainland China.

2. Research Methods

Based on the aforementioned conceptual framework, this section will propose a study on the relationship between the proportion of AI language model design schemes used in work, the degree of evaluation of these schemes, and the additional benefits obtained by employees. We will also select research samples reasonably.

2.1 Research Hypotheses

As our study focuses on regions subject to international internet regulations, we categorize all research subjects into two groups: those who have access to the global internet (Global Group, GG) and those who do not (Local Group, LG). Furthermore, we consider privately-owned or joint-venture enterprises within mainland China to belong to the former category, as they have access to the real international internet, enabling them to better understand external business conditions and reconfigure internal resources to enhance their innovation capabilities and speed of handling time-related matters. On the other hand, institutions within mainland China such as universities, hospitals, research institutes, state-owned enterprises, and government officials belong to the latter category, as they lack access to the international internet, ensuring stable and reliable information sources for internal communication. This helps these institutions maintain a good internal communication foundation, avoid external cooperation or competition, and prevent discussions on the utilization of external resources.

The subjects surveyed in this study are frontline employees who work independently at the lowest level, meaning they do not have colleagues to share the workload in designing schemes. For individuals from privately-owned or joint-venture enterprises within mainland China (GG group), we hypothesize that the design schemes provided by AI language models, leading to increased work efficiency, contribute to their ability to further complete other tasks within the company or save time and effort on current projects, thereby providing recommendations for overall project optimization and implementation. In terms of direct outcomes, this often manifests as an increase in their annual bonuses, with no significant change in opportunities for verbal praise and commendation. Based on these considerations, we propose the following hypotheses:

H1: For employees in the GG group, there is a positive correlation between their involvement with AI language models and an increase in annual bonuses.

H2: For employees in the GG group, there is no significant relationship between their involvement with AI language models and the frequency of receiving praise.

Additionally, for individuals from institutions within mainland China such as state-owned enterprises, government officials, and institutions, belonging to the LG group, we believe that the improvement in work efficiency can help them gain more recognition from their leaders, leading to more job opportunities and promotion chances. However, this may not necessarily translate into a significant increase in bonuses but rather an increase in verbal praise and commendation:

H3: For employees in the LG group, there is no significant relationship between their involvement with AI language models and an increase in annual bonuses.

H4: For employees in the LG group, there is a positive correlation between their involvement with AI language models and an increase in the frequency of receiving praise. When proposing travel route design schemes using AI language models, there may be certain language errors and logical flaws. In cases where there is no supervision, the scheme passes the assessment 100%. However, the more times the initial draft proposed by AI language models undergoes review or discussion before the finalization process, the higher the probability that the scheme needs further refinement, thus reducing the efficiency of both groups. Based on this premise, we propose the following hypotheses:

H5: The number of reviewers or discussions required during the process from the initial draft proposed by AI language models to finalization negatively affects the efficiency of the GG group.

H6: The number of reviewers or discussions required during the process from the initial draft proposed by AI language models to finalization negatively affects the efficiency of the LG group.

2.2 Selection of Research Samples

This study prepared a corresponding questionnaire to obtain the required research data. During the preparation of the questionnaire, it was necessary to develop items related to each variable and select appropriate control variables. The final questionnaire included 13 items related to AI language models, 8 items related to the review hierarchy of scheme design, 6 items related to employee incentives, as well as control variables such as the nature, scale, and establishment time of the workplace [25]. After the initial draft was completed, the questionnaire underwent review and feedback from relevant scholars, and was carefully revised to form the final version. When distributing the questionnaire, 710 frontline employees from various industries in multiple provinces and cities in mainland China were selected. Subsequently, the questionnaire was distributed via email or instant messaging. A total of 683 responses were received, with 629 valid responses, resulting in an effective rate of 92.09%.

3. Result Analysis

Based on the research hypotheses proposed above and the selected research sample, this section will use statistical software IBM SPSS Statistics 26 to conduct data correlation analysis and multiple linear regression analysis on the sample to test the research hypotheses and discuss and analyze the results of hypothesis testing [26].

The mathematical definition formula for factor correlation analysis using the chi-square test is as follows (1):

$$\chi^2 = \sum_{i=1}^{r}\sum_{j=1}^{c}\frac{(f_{ij}^{0}-f_{ij}^{e})^2}{f_{ij}^{e}} \quad \text{(Eq. 1)}$$

where r is the number of rows in the contingency table; c is the number of columns in the contingency table; f_{ij}^{0} is the observed frequency; f_{ij}^{e} is the expected frequency. The formula to calculate the expected frequency f^e is as follows:

$$f^e = \frac{RT}{n}\cdot\frac{CT}{n}\cdot n = \frac{RT\cdot CT}{n} \quad \text{(Eq. 2)}$$

where **RT** is the total sum of row observed frequencies, and **CT** is the total sum of column observed frequencies. According to the above formula, the obtained chi-square statistic reveals that if the expected frequency equals the observed frequency, the minimum chi-square statistic is 0, indicating that the two variables are completely independent and have no correlation. The greater the difference between the expected frequency and the observed frequency, the larger the chi-square statistic obtained, indicating a higher degree of correlation [27].

3.1 Correlation analysis

Based on the research hypotheses proposed above and the collected data, this paper explores the relationship between the proportion of AI language model design schemes used in work, the degree of evaluation of these schemes, and the additional benefits obtained by employees. In the data analysis, we first utilize correlation analysis to determine the dependencies between variables. Tab.1 shows the correlation analysis based on the data derived from GG and LG members, respectively. In the table, correlation coefficients above the 10% level indicate strong correlations between the two variables and are marked with an asterisk (*). It is noteworthy that Tab.1(a) presents data concerning GG members, indicating that the correlation coefficient between Annual Bonus Increase Ratio and Discussion level is 0.372, while with Proportion of AI Usage, it is as high as 0.697. This confirms the accuracy of the previous hypothesis, H1. Additionally, the correlation coefficients between Oral Praises Increase Ratio and the other three variables are all negative and absolute values are less than 5%. This demonstrates that for GG members, oral praises are hardly correlated with other indicators, thus confirming the accuracy of the previous hypothesis, H2.

Table.1 Correlation analysis based on the data derived from GG and LG members, respectively.

(a) GG members	1	2	3	4
1. Discussion Level	1			
2. Proportion of AI Usage	0.510**	1		
3. Annual Bonus Increase Ratio	0.372	0.697**	1	
4. Oral Praises Increase Ratio	-0.043	-0.044	-0.040	1

(b) LG members	1	2	3	4
1. Discussion Level	1			
2. Proportion of AI Usage	0.714**	1		
3. Annual Bonus Increase Ratio	-0.011	0.026	1	
4. Oral Praises Increase Ratio	0.595**	0.700**	0.013	1

P.S. ** represents a significant level above 10%.

Moreover, Tab.1(b) presents data concerning LG members, indicating that the correlation coefficient between Annual Bonus Increase Ratio and Discussion level is -0.011, and with Proportion of AI Usage, it is 0.026, indicating little to no correlation, thus confirming the accuracy of the previous hypothesis, H3. Additionally, the correlation coefficient between Oral Praises Increase Ratio and Discussion Level is 0.595, and with Proportion of AI Usage, it is 0.714, both showing strong correlations, which confirms the accuracy of the previous hypothesis, H4.

From the above, it is evident that in order to describe the quantified indicator of "improved work efficiency", distinctions need to be made for different target populations. If targeting the GG population, then using the Annual Bonus Increase Ratio as a proxy for "work efficiency" is a suitable metric. This is because, in mainland companies, verbal praises often have limited motivational effects on frontline employees, whereas monetary rewards or bonuses are typically the primary or most significant incentives. Conversely, for the LG population, "Oral Praises Increase Ratio" can serve as a proxy for their "work efficiency". This is because public servants are not allowed to receive additional monetary rewards, and in such cases, praises from leaders are often the only and most effective means of recognition within the system.

However, the above correlation analysis only describes the degree of closeness between "work efficiency" (Annual Bonus Increase Ratio for the GG target population; Oral Praises Increase Ratio for the LG target population, as mentioned earlier) and Discussion Level and Proportion of AI Usage, without determining the specific interaction between variables. Additionally, it is worth noting that the correlation coefficients of Discussion Level with "work efficiency" for both the GG and LG groups are 0.372 and 0.595, respectively. This means that Discussion Level has a positive influence on "work efficiency" for both groups. Therefore, the previous hypotheses H5 and H6 are incorrect. To further comprehensively evaluate, we need to conduct multiple linear regression analysis [28].

3.2 Multiple linear regression *analysis*

Regression analysis allows for the inference of one variable from another, describing the interaction between multiple variables' changes. In regression analysis, we first tested the linear regression relationship of "work efficiency" for the GG group, i.e., using Annual Bonus Increase Ratio as the dependent variable and Discussion Level and Proportion of AI Usage as the independent variables. The obtained R-squared value is 0.487, indicating that, to some extent, 48.7% of the Annual Bonus Increase Ratio from the GG group's study results can be explained by Discussion Level and Proportion of AI Usage.

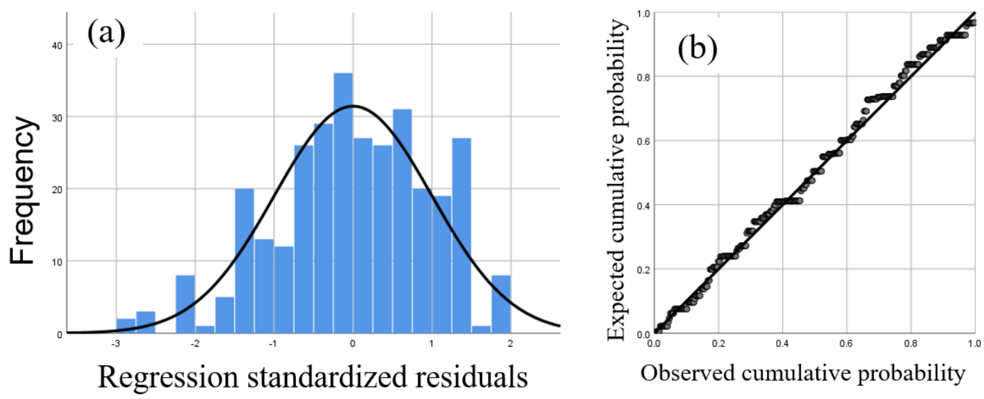

Figure 1. (a) histograms of frequency versus regression standardized residuals and (b) normal P-P plots of expected cumulative probability versus observed cumulative probability for the GG group.

Figure 1 respectively presents histograms of frequency versus regression standardized residuals, as well as normal P-P plots of expected cumulative probability versus observed cumulative probability.

As shown, the regression standardized residuals exhibit a well-normal distribution, and there is an almost perfect linear relationship between expected cumulative probability and observed cumulative probability. Therefore, it can be concluded that for employees in the GG group, the data indicator of Annual Bonus Increase Ratio can be used to quantify work efficiency, and it exhibits a good linear regression relationship with Discussion Level and Proportion of AI Usage.

Figure 2 presents histograms of frequency versus regression standardized residuals and normal P-P plots of expected cumulative probability versus observed cumulative probability for the LG group's work efficiency, where Oral Praises Increase Ratio serves as the dependent variable. Compared to Figure 1, it can be observed that the distribution of regression standardized residuals is more concentrated, but the linear relationship between expected cumulative probability and observed cumulative probability is not as precise as in the GG group's data. This is because the frequency of oral praises can be influenced by memory biases during the statistical process, thus affecting the accuracy of the data. In contrast, the data in Figure 1 is based on reliable monetary figures as indicators, hence it is more credible.

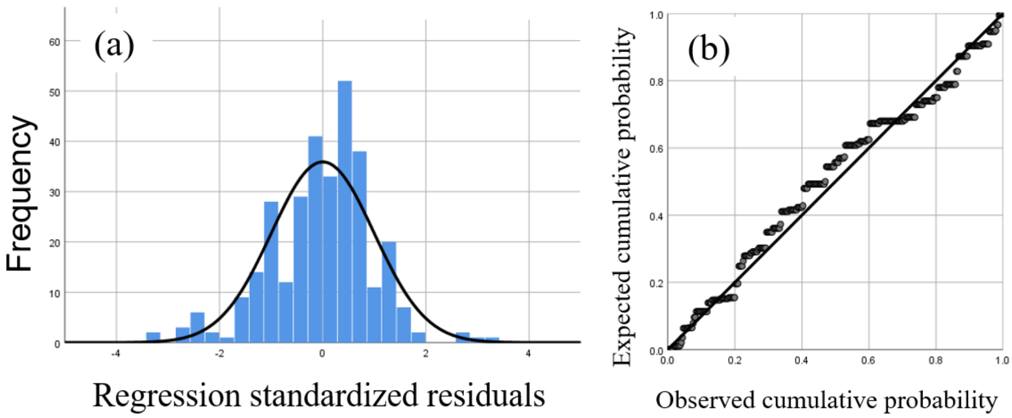

Figure 2. (a) histograms of frequency versus regression standardized residuals and (b) normal P-P plots of expected cumulative probability versus observed cumulative probability for the LG group.

3.3 Intuitive *Analysis*

As demonstrated earlier, for the GG and LG groups, Annual Bonus Increase Ratio and Oral Praises Increase Ratio respectively serve as proxies for Efficiency. By standardizing the Efficiency coordinates and using its values as the Z-axis, while utilizing Discussion Level and Proportion of AI Usage as the X-axis and Y-axis respectively, contour plots are employed to intuitively illustrate the influence of these two factors on Efficiency. Unlike the multivariate linear regression used earlier for estimating Efficiency, Figures 3(a) and (b) visually display the distribution of Efficiency in the GG and LG groups, respectively, concerning the use of AI-generated design proposals.

It is noteworthy that for the GG group, the maximum Efficiency occurs at approximately Discussion level=3 and Proportion of AI Usage=70. Due to the current imperfections of AI models, employees cannot rely entirely on AI-generated content. Our research results suggest that the optimal value for Proportion of AI Usage is around 70%. Regarding Discussion level=3, one possible explanation is that, for the GG group, it can be assumed that every employee has access to AI language models, possesses the experience, and the ability to discern the AI components in design proposals. Therefore, as the Discussion level increases, more people engage in discussions, resulting in a decrease in AI efficiency.

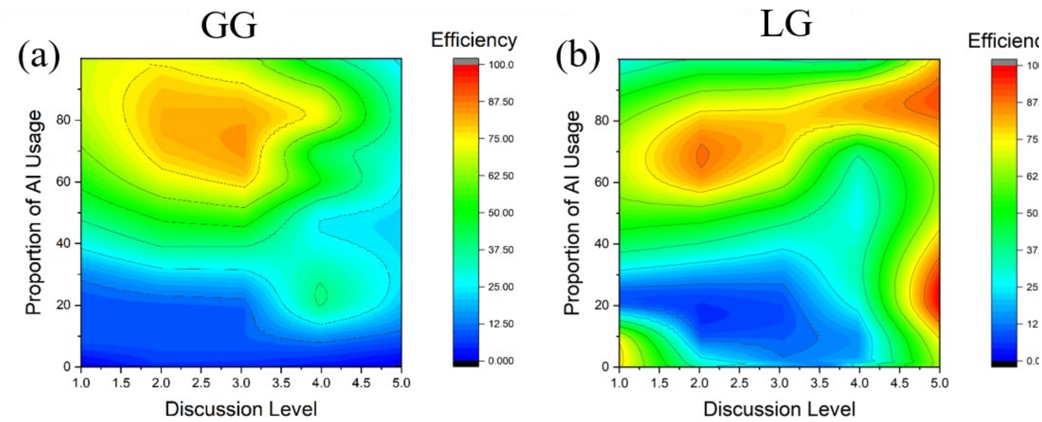

Figure 3. Distribution of Efficiency in the (a) GG and (b) LG groups, respectively, concerning the use of AI-generated design proposals.

It is worth noting that the Efficiency situation of the LG group, as shown in Figure 3(b), exhibits a multi-modal distribution. The peak values of Efficiency occur in three regions: (2, 68), (5, 89), and (5, 23). This implies that for lower levels of Discussion level, around 70% Proportion of AI Usage is a reasonable value. However, for higher levels of Discussion level (=5, involving at least five rounds of research discussions), proportions of around 20% and 80% Proportion of AI Usage are more prominent. This is because the LG group leaders involved in the discussion cannot access AI-assisted models, or, in a sense, such AI-assisted generated content does not exist within their cognition. Therefore, with more participants in the Discussion, it is easier to receive positive evaluations of the current draft. An 80% Proportion of AI Usage indicates that the AI-generated content still needs human intervention to further improve. Interestingly, around 20% Proportion of AI Usage still achieves a sufficiently high Efficiency under high levels of Discussion level. This suggests that for the design documents required by the LG group, such as those related to political studies, most of them cannot be generated by the current unverified AI-assisted systems, leading to the need for employees to write most of the content themselves. In this case, only 20% AI assistance is needed to reach the peak Efficiency. Of course, if we backtrack the data, there is also a possibility that LG employees deliberately reduce the level of Proportion of AI Usage during the investigation process.

4. Conclusion

In conclusion, this study investigated the relationship between the usage of AI language models in workplace design solutions, the evaluation level of these solutions, and the additional benefits obtained by employees. Through statistical analyses, we explored the impact of Discussion Level and Proportion of AI Usage on Efficiency, represented by Annual Bonus Increase Ratio for the GG group and Oral Praises Increase Ratio for the LG group. For the GG group, it was found that Annual Bonus Increase Ratio positively correlated with both Discussion Level and Proportion of AI Usage. This suggests that, within mainland companies, monetary incentives are the primary motivators for employees, while AI usage significantly contributes to efficiency, particularly when Discussion Level is high.

Conversely, for the LG group, Oral Praises Increase Ratio exhibited a different pattern. The results indicated that Discussion Level positively influenced efficiency, while the impact of Proportion of AI Usage was less pronounced. This suggests that, within public institutions where monetary rewards are limited, verbal praise from superiors plays a more significant role in motivating employees. Additionally, the effectiveness of AI assistance in generating documents varied based on the level of Discussion. Higher levels of Discussion led to more favorable evaluations, indicating a need for human intervention to refine AI-generated content, especially in politically sensitive contexts.

Moreover, the graphical analysis revealed distinct trends in Efficiency distribution for both groups. For the GG group, Efficiency peaked at a Proportion of AI Usage of around 70%, while for the LG group, multiple peaks were observed, reflecting different preferences and constraints in utilizing AI-assisted solutions.

In summary, this research provides insights into the complex interplay between AI language model usage, workplace efficiency, and employee motivation in different organizational settings. By understanding these dynamics, organizations can better harness AI technologies to optimize workflow and enhance employee performance. Further studies could explore additional factors influencing the adoption and effectiveness of AI language models in diverse workplace environments.

Data Availability

The data supporting the findings of this study are accessible upon request from the author.

Conflict of Interest Statement

The author affirms that there are no conflicts of interest.

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