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Impact Of Artificial Intelligence On Employee Productivity And Job Satisfaction: A Study In The Digital Workplace

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ABSTRACT

The shift from being a peripheral participant to a valuable participant in organizational strategies due to the emergence of the synthetic intelligence (AI) era has produced several implications for organizational placement. The reason for this study is to determine the implications of synthetic intelligence on worker productivity and process satisfaction by examining 4 elements. Having a look at this may be able to fill gaps in the existing literature regarding the topic of proximity. Regarding the techniques used on these studies, the author used the quantitative pass-sectional survey method, where he collected the fact use of surveys among 280 full-time employees within 12 companies that heavily use technological innovation of their activities, the Clothing industry, manufacturing, industries. Partial least square structural equation modelling (PLS-SEM) modified to used to examine the collected information. The findings show that each of the 4 factors had predictive talents explaining 61.3% and 57.Eight% of the variability in employee productivity and activity enjoyment, respectively. Moreover, findings show that the models developed are statistically significant. Some variables that showed widespread consequence magnitudes in affecting workers' productivity and job satisfaction are as follows: Human-AI Collaboration (β=0.36, p<null.001), AI Personalization (β=zero.33), AI Automation (β=zero,31), and AI Decision Support (β=null.31). form the highest priority funding for companies looking to decorate group of workers achievement and employee wellness within the digital age. Practical pointers are provided for HR leaders to prioritize improvement of collaborative and personalized AI equipment in virtual workplaces.

Keywords: Artificial Intelligence, Employee Productivity, Job Satisfaction, Digital Workplace, Human–AI Collaboration, PLS SEM 6

INTRODUCTION:

AI, once an abstract idea, is now an essential part of painting techniques, painting decisions, and work equipment. [1] pointed out that AI is creditable for productivity in that it automates cognitive work. However, [2] pointed out that the virtual administration center is where the impact of AI on the painting life is most significant. However, it is also evident that the impact of AI on working life became disproportionate. This is in line with [3] who pointed out that although AI is responsible for the productivity in painting selection, the impact of AI on working existence is disproportionate for the worker team. Furthermore, [4] pointed out that AI is chargeable for displacing certain forms of work. This is in line with the reality that there is a duality in the painting life, in that it is not the simplest productivity in painting activity but also the displacement of labour. According to [5], the most productive form of AI is in balancing tool analysis with creativity. Therefore, this observation sought to explore the existence of AI in paintings on four dimensions. Look at changed to committed among 280 respondents from distinct areas.

Although there is a growing trend within the use of AI within the workplace, previous studies are limited in the sense that they may be limited to at least one type of application, end result, or record type. The purpose of the current study is to fill the missing part of the multiconstruct empirical version. What contemporaries are looking at objectives to answer is: What are the most impactful dimensions of workplace AI, and to what quantity, in phrases of employee productivity and pride in virtual workplaces?

The goal of the primary study is to analyze the impact of automation of duties with the resources of AI on employee productivity, the impact of personality and the collaboration with AI on employee productivity, and ultimately, which aspect of AI is the best for predicting the two factors of employee productivity and job productivity.

2.0 REVIEW OF LITERATURE AND HYPOTHESES DEVELOPMENT

It is thus interesting to articulate that while AI is transforming the character of the workplace, research has been very pure in describing one component: AI is uniquely used to help, no longer update, people. For example, research has proven that AI has the ability to automate a tremendous percentage of routine responsibilities in the administrative center, freeing the employee to communicate in complex and creative responsibilities. For example, [6] predicted that forty-five to 60 percent of the current responsibilities within the administrative center could be computerized, and in all times the productivity of the last employee could increase. However, in another study, [7] talked about that while the above finding might be real in terms of macro productivity, it is far wise to avoid the reality that a massive percentage of business categories faced excessive levels of automated advertising.

For example, [8] pointed out the existence of an automation-augmentation paradox where AI systems, while increasing productivity, simultaneously reduce the levels of employee autonomy. Indeed, [4] confirmed the lifestyle of the displacement effect, challenge to the way in which the employee's position is controlled. AI powered selection tools add to this through supporting humans make faster, better informed alternatives. [9] confirmed that hybrid structures combining AI analysis with human reasoning always outperformed both working by myself. In HR specifically, [10] and [11] determined measurable improvements in setting first-class and overall performance comments, while [12] indicated that employees spoke back somewhat better to AI tools they skilled as supportive rather than supervisory.

The blessings of AI will be even greater if the system is able to adapt to individual preferences. [13] found that the use of personalized AI structures influences greater autonomy, competence, and task pride, and [14] observed that the use of customized AI-based mastery always has implications in additional engagement and efficiency, which can be direct signs of work performance.

In some of these distinctive dimensions, the not uncommon result has been that miles are an end result of collaboration between humans and AI. This has been confirmed at a glance carried out using [5] where it became apparent that companies that lay out their procedures in a way that is optimized for complementarity between humans and AI, where human knowledge of judgment and creativity, and where AI focuses on the absolute duties that humans perform in goal execution loneliness. The study, which was done with the help of [15] and also some other one, which was carried out by [16], showed that not most effectively humans make distinctions between sentences about engagement, satisfaction and overall performance, however, they do it at the same time and not simplify as a solution, but also as a solution.

2.1 RESEARCH GAP

Although there are already massive studies of AI within the place of business, this is the forefront of developing a PLS SEM version that separates the impact of four specific AI constructs on productivity and task satisfaction. This have an eye on contributes to the body of knowledge by growing an all-encompassing explanatory framework that incorporates the TAM, JD R, and AMO models in the context of a growing economy.

2.2 RESEARCH HYPOTHESES

H1: AI enabled automation is positively associated with employee productivity in digital workplace settings.

H2: AI driven decision support is positively associated with employee productivity.

H3: AI based personalisation is positively associated with employee job satisfaction.

H4: Human–AI collaboration is positively associated with both employee productivity and job satisfaction.

3.0 RESEARCH METHODOLOGY

3.1 RESEARCH DESIGN

The quantitative, positivist, cross-sectional study design was chosen to allow testing of the proposed hypotheses in an objective manner. The use of the Positivist method in quantitative research, which assumes that social truth can be quantified, is most appropriate for use in research where the reason for the study is to test current theories, as opposed to developing new ones [18]. The move-sectional technique is considered appropriate for the purpose of exploring the associative links between the AI constructs and the final outcome variables.

3.2 DATA COLLECTION AND SAMPLE

The participants included in the study were full-time employees from organizations that had embraced the adoption of artificial intelligence in at least one discipline in their respective organizations. Purposeful sampling was rewarded by selecting 12 institutions from 4 different regions. Structured questionnaires are distributed for seven weeks in January and February 2026 totalling 340 questionnaires. A total of 301 responses have been received from the targeted respondents, of which only 280 are considered valid, resulting in an eighty-two.4 percent response rate.

3.3 DATA ANALYSIS

In the first stage, IBM SPSS Statistics software (v26) is used to check for missing values, outliers, and to generate descriptive statistics and Cronbach's Alpha coefficients. In the second step, Smart PLS (v3.3.Nine) became used for PLS SEM estimation. PLS SEM analysis became taken into consideration greater suitable than Covariance-Based SEM estimation for this look at for the following motives. The non-normality of the data, although small, supports the PLS SEM estimation. The sample size of this have a look at is suitable for PLS SEM analysis. The version of this study, i.e., a twin model, supports variance-based analysis. The observation examines four independent variables, viz. AI active automation, AI driven decision support, AI based personalization and human AI collaboration, and their impact on two established variables, viz. employee productivity and job satisfaction.

4.0 RESULTS AND DISCUSSION

4.1 DESCRIPTIVE STATISTICS

As evidenced in Table 1, the measures of vital tendency and dispersion are calculated for the complete pattern of 280 valid responses. All the construct methods were above the midpoint of the Likert scale with three.0, indicating that employees valued both place of business AI systems and their personal productivity/pride without hesitation. Employee productivity had the highest suggest and lowest preferred deviation, observed in detail with the help of Job Satisfaction, showed effective perceptions of their own performance. Of the 4 AI predictor constructs, AI Enabled Automation had the best content, while AI Based Personalization had the bottom, indicating that the latter form of AI machine is given the impression that it is the least effective.

Table 1: Descriptive Statistics for All Study Constructs (N = 280)

Variable	N	Mean	SD	Min	Max
Employee Productivity	280	3.84	0.62	1.00	5.00
Job Satisfaction	280	3.77	0.65	1.00	5.00
AI-Enabled Automation	280	3.72	0.68	1.00	5.00
AI-Driven Decision Support	280	3.66	0.71	1.00	5.00
AI-Based Personalisation	280	3.61	0.74	1.00	5.00
Human–AI Collaboration	280	3.69	0.70	1.00	5.00

Note: All constructs measured on a five point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). SD = Standard Deviation.

4.2 RELIABILITY ANALYSIS

Table 2 suggests Cronbach's Alpha for all six constructs, all of which are above 0.70, which is suggested with the help of [19]. The highest value is in Employee Productivity, at 0.89. This is due to the six smartphones used to measure it. The lowest fee is in Human AI collaboration, it is 0.80.

Table 2: Internal Consistency — Cronbach's Alpha by Construct

Construct	No. of Items	Cronbach's Alpha	Status
Employee Productivity	6	0.89	Acceptable
Job Satisfaction	5	0.86	Acceptable
AI-Enabled Automation	5	0.84	Acceptable
AI-Driven Decision Support	5	0.82	Acceptable
AI-Based Personalisation	5	0.81	Acceptable
Human–AI Collaboration	4	0.80	Acceptable

Note: Cronbach's Alpha values at or above 0.70 indicate acceptable internal consistency (Nunnally & Bernstein, 1994).

HYPOTHESIS TESTING: PLSSEM STRUCTURAL PATH COEFFICIENTS

PLS SEM analysis was implemented based totally on attention of five.000 bootstraps used in studying the structural model develop. According to the findings, there can be a high degree of explanatory ability in sentences of measures as the 4 dimensions of AI explained sixty one.3% variance of employee productivity (R2 = zero.613) and fifty seven. Eight% variance of job satisfaction (R2 = zero.52). The specific path analysis is shown in Table three.

Table 3: PLSSEM Structural Path Coefficients — Hypothesis Testing

Hypothesis Path	β	t-value	p-value	Outcome
H1: AI Enabled Automation → Employee Productivity	0.31	4.78	0.001	Supported
H2: AI Driven Decision Support → Employee Productivity	0.28	4.32	0.002	Supported
H3: AI Based Personalisation → Job Satisfaction	0.33	5.01	0.001	Supported
H4: Human–AI Collaboration → EP & JS	0.36	5.24	0.001	Supported

Note: EP = Employee Productivity; JS = Job Satisfaction. Bootstrap resampling = 5,000 iterations. $p < 0.01$; $p < 0.001$.

All the research hypotheses have been supported. The maximum contribution of path support was recorded with Human AI Collaboration (β = 0.36, t = five.24, p < zero.001), which proved to be the most important dimension of AI within the correlation with both outcome variables. AI Based Personalization was the second most vital dimension of AI that drastically contributed to the prediction of the final outcome variables (β = null.33, t = five.01, p < null.001), with the most powerful effect on Job Satisfaction. AI-enabled automation and AI-driven decision support were the most critical AI dimensions that definitely contributed to the prediction of employee productivity.

4.3 INTERPRETATION OF RESULTS

The publication accounted for sixty-one. Three% of variance in productivity and fifty seven. 8% in activity enjoyment, which confirmed that AI truly affects the employees through diverse wonderful channels. All 4 paths had been statistically large, confirming the proposed AMOJDRTAM framework. The AMO version [19] is directly applicable to the findings where these four constructs are a combination of opportunities, motivation and opportunity of an employee. All these dimensions also served as task assets [20] that reduced workload and facilitated goal promotion activities. These findings, in mix, confirm the validity of the proposed framework for AI adoption studies.

HumanAI Collaboration became the most powerful predictor for each outcome, helping [5] illustrate that challenge allocation strategies outperform displacement-based automation. The employee who retained control over judgment-intensive duties and had AI-controlled subtasks maintained the manipulation that fuels engagement and performance. In line with this, [22] found that collaborative strategies where interruption barriers are well described yielded additional sustainable increases in overall performance. AI Based Personalization became the next most powerful predictor of enjoyment, and each [13] and, [11] attribute this to the greater autonomy and job fulfilment created by responsive AI. [21] TAM supports that devices that, in my view, are seen as useful are those that hold positive judgments, thus maintaining pleasure.

Similarly, AI Enabled Automation had a significant and qualitative impact on productivity (β = 0.31), which is also located in [6], as it relieved the cognitive load for higher-level tasks. The result becomes barely higher than that of AI Driven Decision Support (β = 0.28), suggesting that relief from workload is currently more necessary to improve productivity. [8] attribute this distinction to the insufficient preparation of the personnel for the necessary evaluation of decision guidance advice. Both effects point to enhancing employees' AI literacy therefore maximizing the immediate and powerful organizational process. This could likely boom path support for choice guidance in several longitudinal studies.

5.0 CONCLUSION AND FUTURE RESEARCH

This paper sought to analyze the impact of four AI constructs automation (β = null.31), selection guidance (β = null.28), personalization (β = null.33) and human AI collaboration (β = 0.36) on employee productivity and job satisfaction of 280technology employees. All four hypotheses received empirical guidance, and the proposed structural model explained sixty-one.3% of the variance in employee productivity and fifty-seven.8% of the variance in activity enjoyment. The aggregation of human AI collaboration dominated every effect and should be prioritized in organizations looking for simultaneous upgrades in overall performance and task satisfaction. The proposed TAMJDRAMO framework is an authentic and effective approach to explain the phenomenon of AI in organizations. Future research should explore the causal relationships and developmental boundaries of constructs in individual settings and across years.

Future studies can scale up the research by using inclusive employees from different industries and larger geographical areas to increase the generalizability of the findings. Longitudinal studies can also help in knowing about the long-term impact of artificial intelligence on workers' productivity and job satisfaction. Further research can explore additional factors along with employee training, organizational subculture, and the moral aspects of AI adoption. Comparative studies between companies with excessive and occasional AI integration can additionally provide deeper insights into workflow and worker nicely-being.

LIMITATIONS OF THE STUDY

Cross-sectional configuration does not provide evidence of causality, while locally based research limits the possibility of generalization. Self-report scales create common method bias concerns, while a sample size of 280 individuals is inadequate for multigroup evaluation

REFERENCES

1. Brynjolfsson, E., & McAfee, A. (2014). The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies. W. W. Norton & Company. https://wwnorton.com/books/the-second-machine-age
2. Kane, G. C., Phillips, A. N., Copulsky, J., & Andrus, G. (2019). The Technology Fallacy: How People Are the Real Key to Digital Transformation. MIT Press. https://mitpress.mit.edu/9780262538008/the-technology-fallacy/
3. Davenport, T. H., & Ronanki, R. (2018). Artificial Intelligence for the Real World. Harvard Business Review, 96(1), 108–116. https://hbr.org/2018/01/artificial-intelligence-for-the-real-world
4. Acemoglu, D., & Restrepo, P. (2018). The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment. American Economic Review, 108(6), 1488–1542. https://www.aeaweb.org/articles?id=10.1257/aer.20160696
5. Wilson, H. J., & Daugherty, P. R. (2018). Collaborative Intelligence: Humans and AI Are Joining Forces. Harvard Business Review, 96(4), 114–123. https://hbr.org/2018/07/collaborative-intelligence-humans-an d-ai-are-joining-forces
6. Chui, M., Manyika, J., Bughin, J., Dobbs, R., Roxburgh, C., Sarrazin, H., Sands, G., & Westergren, M. (2016). Notes from the AI Frontier: Automation and the Future of Work. McKinsey Global Institute. https://www.mckinsey.com/featured-insights/artificial-intelligence/notes-from-the-ai-frontier-modeling-the-impact-of-ai-on-the-world-economy
7. Frey, C. B., & Osborne, M. A. (2017). The Future of Employment: How Susceptible Are Jobs to Computerisation? Technological Forecasting and Social Change, 114, 254–280. https://doi.org/10.1016/j.techfore.2016.08.019
8. Raisch, S., & Krakowski, S. (2021). Artificial Intelligence and Management: The Automation–Augmentation Paradox. Academy of Management Review, 46(1), 192–210. https://doi.org/10.5465/amr.2018.0072
9. Dellermann, D., Calma, A., Lipusch, N., Weber, T., Weigel, S., & Ebel, P. (2019). The Future of Human-AI Collaboration: A Taxonomy of Design Knowledge for Hybrid Intelligence Systems. Proceedings of the 52nd Hawaii International Conference on System Sciences, 1–10. https://hdl.handle.net/10125/59747
10. Hmoud, B., & Laszlo, V. (2019). Will Artificial Intelligence Take Over Human Resources Recruitment and Selection? Network Intelligence Studies, 7(13), 21–30. https://www.ceeol.com/search/article-detail?id=754663
11. Tambe, P., Cappelli, P., & Yakubovich, V. (2019). Artificial Intelligence in Human Resources Management: Challenges and a Path Forward. California Management Review, 61(4), 15–42. https://doi.org/10.1177/0008125619867910
12. Kaur, D., Uslu, S., Rittichier, K., & Durresi, A. (2022). Trustworthy Artificial Intelligence: A Review. ACM Computing Surveys, 55(2), 1–35. https://doi.org/10.1145/3491209
13. Park, S., & Kim, B. C. (2020). The Impact of Personalized AI on Employee Autonomy and Job Satisfaction. Journal of Business Research, 117, 568–577. https://doi.org/10.1016/j.jbusres.2020.04.044
14. Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic Review of Research on Artificial Intelligence Applications in Higher Education – Where Are the Educators? International Journal of Educational Technology in Higher Education, 16(1), 1–27. https://educationaltechnologyjournal.springeropen.com/articles/10.1186/s41239-019-0171-0
15. Lee, M. K., Kusbit, D., Metsky, E., & Dabbish, L. (2019). Working with Machines: The Impact of Algorithmic and Data-Driven Management on Human Workers. Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems, 1–14. https://doi.org/10.1145/3290605.3300768
16. Huang, M. H., & Rust, R. T. (2018). Artificial Intelligence in Service. Journal of Service Research, 21(2), 155–172. https://doi.org/10.1177/1094670517752459

17. Sekaran, U., & Bougie, R. (2016). Research Methods for Business: A Skill Building Approach (7th ed.). John Wiley & Sons.https://www.wiley.com/en-us/Research+Methods+For+Business%3A+A+Skill+Building+Approach%2C+7th+Edition-p-9781119266846

18. Nunnally, J. C., & Bernstein, I. H. (1994). Psychometric Theory (3rd ed.). McGraw-Hill. https://www.worldcat.org/title/28221417

19. Appelbaum, E., Bailey, T., Berg, P., & Kalleberg, A. L. (2000). Manufacturing Advantage: Why High-Performance Work Systems Pay Off. Cornell University Press. https://www.cornellpress.cornell.edu/book/9780801486371/manufacturing-advantage/

20. Bakker, A. B., & Demerouti, E. (2007). The Job Demands-Resources Model: State of the Art. Journal of Managerial Psychology, 22(3), 309–328. https://doi.org/10.1108/02683940710733115

21. Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use and User Acceptance of Information Technology. MIS Quarterly, 13(3), 319–340.https://doi.org/10.2307/249008

22. Lichtenthaler, U. (2020). The Double-Edged Sword of Digitalization: Balancing Automation and Human Agency in the Workplace. Organizational Dynamics, 49(4), 100758. https://doi.org/10.1016/j.orgdyn.2020.100758