

**AI-Driven Work Design and Enterprise Sustainability: Insight from Emerging Economy****Samuel Ayodele MAJEKODUNMI (Ph.D)<sup>1</sup>, Emmanuel Yinka, ADEWUNI<sup>2</sup>****Department of Business Administration, Osun State University, Osogbo, Nigeria****ABSTRACT**

This study investigates the influence of AI-Driven Work Design (AI-DWD) on Enterprise Sustainability (ES). Determinants of AI-DWD explored in this work are AI-Driven Task Automation (AI-DTA), AI-Supported Decision Making (AI-SDM), and AI-Enabled Work Redesign (AI-EWR); while the determinants of ES explored include Economic Sustainability (EcS), Environmental Sustainability (EnS), and Social Sustainability (SoS). **Purpose:** This research is required to fill existing gap of low exploration of AI-DWD and ES in the context of emerging economies. Accordingly, this research addresses threats associated with ES in banking industry, using case of Selected Bank (SB) firm. **Method:** An empirical survey was conducted, using SB, a firm known for technological inclination. Data were analysed using 29th version of SPSS to derive F-Statistic (F-S) of joint influence of AI-DTA, AI-SDM, and AI-EWR on respective determinants of ES. **Results:** AI-DTA, AI-SDM, and AI-EWR reveal a jointly significant influence on EcS. More so, AI-DTA, AI-SDM, and AI-EWR show jointly significant influence on SoS. However, AI-DTA, AI-SDM, and AI-EWR demonstrate jointly insignificant influence on EnS. **Contributions:** First, this research conceptualizes joint influence of AI-DTA, AI-SDM, and AI-EWR on each determinant of ES. Second, this paper makes an empirical contribution by breaking down AI-work design into AI-DTA, AI-SDM, and AI-EWR, and thus shows how distinct AI work practices influence different aspects of ES. Third, it adds to methodological literature by exploring F-S component of Multiple Regression (MR) analyses. Consequently, this study provides insights that serve as guide to managers, policymakers, and scholars.

**Keywords:** Artificial intelligence (AI); enterprise sustainability; AI-driven task automation; AI-supported decision making; AI-enabled work redesign; economic sustainability; environmental sustainability; F-Statistic; socio-technical systems

## 1. INTRODUCTION

The fast development of AI has underpinned one of the largest transformative technological effects on 21st century, reshaping how organisations work, compete, and deliver value. However, exploration in the context of AI-Driven Work Design (AI-DWD) and Enterprise Sustainability (ES) still remains unpopular. This unpopularity is more pronounced in the emerging economies.

Extant research addressed broad topics, like the adoption of AI, digital transformation [18]. More specifically, interactions have been assessed between FinTech, firm innovation, and Environmental, Social and Governance (ESG) performance [1, 13]. Although research findings from such investigations are helpful regarding AI application, relatively few studies have treated AI-based work design that includes AI-based task automation, AI-assisted decision-making, and AI-enabled workflow redesign. Moreover, existing studies failed to project construct of enterprise sustainability, which considers economic sustainability, environmental sustainability, and social sustainability. As a result, there is a scarcity of empirical evidence illustrating the collective effects of AI-DWD on ES.

In advanced economies, policymakers are already benefiting from recommendations that arose from researchers' findings on machine learning, robotic process automation (RPA), predictive analytics, intelligent chatbots, and generative AI to improve operational efficiency, long-term organisational competitiveness, and resilience [5]. In contrast, most studies in emerging economies still revolve around traditional business process re-engineering and corporate social responsibility (CSR). Accordingly, purpose of this study is to address gap relating to limited exploration of AI-DWD and ES. Consequently, problems of non-available of empirical recommendations for policymakers and industrialists on issues relating to AI-DWD and ES receives a demystifying investigation. Moreover, this study offers an opportunity for policymakers and industrialists to explore recommendations that emanate, and thereby improve resource use, increase operational efficiency, enhance risk management, minimize waste, and promote evidence-based decision-making.

## 2. Literature review and hypotheses development

### 2.1 AI-Driven Work Design (AI-DWD) and Economic Sustainability (ES)

In empirical-based research, [7] investigated the effect of AI adoption (AI-A) on corporate sustainability performance (CSP). Results suggested that organizational change moderated the impact of AI on CSP. However, the study mainly focused on AI-A without addressing AI-EWR as a multi-dimensional concept consisting of AI-DTA, AI-SDM, and AI-EWR. Moreover, [14] examined role of AI on sustainable banking (SuB) performance in China. Results revealed that AI had a strongest positive effect on organisational learning; organisational learning was positively related to institutional resilience; and institutional resilience was positively related to long-term organisational performance. This research demonstrates that application of AI ensures sustained growth of an organisation. However, this study ignored economic sustainability.

Moreover, [13] explored effect of AI on learning organisation (LO) and SuB in Turkey. Results show that AI-enabled decision support and AI-enabled workflow redesign significantly increase employee and organisational learning, service quality, and innovation capability. However, that research was concentrated on organisational learning and SuB without overtly quantifying economic sustainability measures of profitability and efficiency of operations. Given the awareness of how AI dimensions contribute to performance of organisations, a positive interaction is envisaged between AI-DWD and ES.

H<sub>1</sub>: AI-DTA, AI-SDM, and AI-EWR have significant joint influence on EcS.

### 2.2 AI-Driven Work Design and Environmental Sustainability

AI-DWD has emerged as a vital lever for realising operational excellence and maintaining a competitive advantage [5-7]. Moreover, [10] states that design of work in an era of AI includes restructuring of jobs and work environment to facilitate interaction of humans with intelligent technologies in a manner that supports employees' well-being and effectiveness of organisation. AI-driven work design reshapes organisational work via redistribution of work tasks between human and intelligent systems, influencing occupations, managerial conduct, and organisational structures [6]. At the same time, firms must offer education, change management, and supportive leadership to promote workforce adjustability in AI-empowered workspaces [11]. Human-AI collaboration improves decision quality, reduces operational risks, enhances customer satisfaction, and strengthens organisational performance [5].

Empirically, [1] studied the effect of AI adoption on Environmental, Social, and Governance. Results indicated that AI-A greatly improved environmental sustainability. This investigation established that work systems based on AI allow banks to factor sustainability into strategic and operational decisions. But the analysis highlighted AI-A in a generic way and ignored the conceptualisation of AI-DTA, AI-SDM, and AI-EWR. Considering the information on responsiveness of AI components in resolving business environment challenges, a positive influence is foreseen between AI-DWD and ES.

H<sub>2</sub>: AI-DTA, AI-SDM, and AI-EWR have significant joint influence on EnS.

### 2.3 AI-Driven Work Design and Social Sustainability

Recently, there have been transformative technologies that have potential to help organisations continue on their sustainability journey [17]. Moreover, through enhanced operational efficiency, enable intelligent use of resources, minimized environmental impact, and increase engagement with stakeholders, such as AI, big data analytics, cloud computing and digital transformation [11-13].

Traditional job design has been greatly changed through the use of AI in redefining tasks of employees [16]. Moreover, in view of their skills, workflows, and relationships within organisation. Therefore, human resource managers are increasingly focusing on employee reskilling and upskilling initiatives to prepare the workforce for digital transformation [8]. Design of work for AI becomes a lever for transformation of entire organisation. Hence, this leads to organisations being more proactive rather than reactive towards competitive challenges [12]. AI-driven work design is a vital means to deliver business success and promote economic, environmental, and social sustainability as a supplement to strengthening operational excellence [7].

In an extant study, [14] focused on effects of AI-A on SuB in the banking sector of China. The research employed a mixed-methods approach. Results indicated that decision-making based on AI and workflow reconstruction positively affected the flexibility of employees, organisational creativity, customer satisfaction, and the resilience of institutions. This study mainly focused on environmental sustainability with limited empirical attention on social sustainability aspect. Due to evidence on AI measures' relevance in navigation issues relating to business, a positive influence is expected; a positive influence is foreseen between AI-DWD and ES.

H<sub>3</sub>: AI-DTA, AI-SDM, and AI-EWR have a significant joint influence on SoS.

## 2.4 Conceptualisation of research model

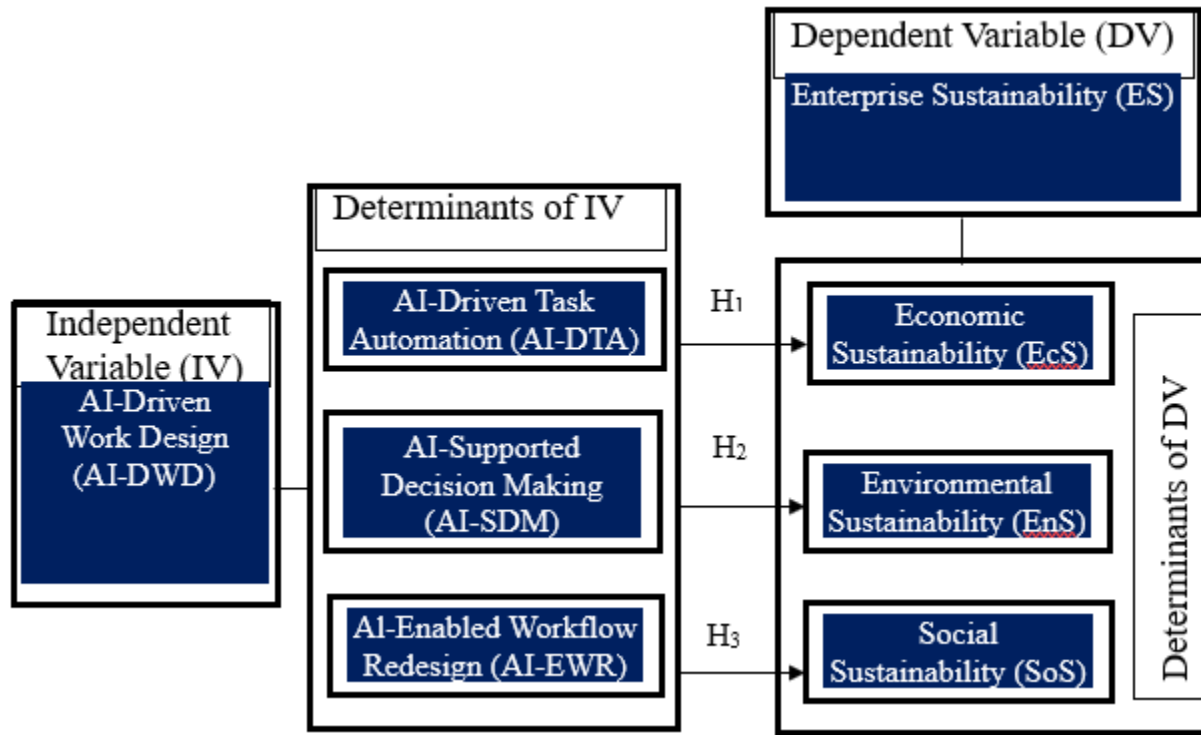


Fig. Research model for AI-DWD, and ES

Source: Developed by the authors

## 3. Material and methods

### 3.1 Research context, sampling, and measurement procedures

This study adopted a survey research design. Population for this study comprises all employees of Selected Bank (SB). SB employees are directly involved in implementing and using AI-driven work systems. Accordingly, employees across different functional departments, including Operations (Op), Information Technology (IT), Customer Service (CS), Human Resource Management (HRM), and Digital Banking (DB) units constitute potential participants. Population of employees is 500.

Sample size for this study was determined using Taro Yamane's (1967) formula:

$$n = \frac{N}{1 + N(e)^2}$$

Where:

- $n$ = Sample size
- $N$ = Population size
- $e$ = Level of precision (5% or 0.05)

$$n = \frac{500}{1 + 500(0.05)^2}$$

$$n = \frac{500}{1 + 500(0.0025)}$$

$$n = \frac{500}{1 + 1.25}$$

$$n = \frac{500}{2.25}$$

$$n = 222.22 \approx 222$$

This study adopted a multistage sampling technique, comprising purposive and simple random sampling, to select respondents. In the first stage, purposive sampling was employed to select SB because it is one of Nigeria's leading financial institutions with substantial investments in AI technologies and digital transformation initiatives. It has integrated AI into various operational areas, including CS, fraud detection, credit risk assessment, DB, and workflow management, making it suitable for investigating influence of AI-DWD on ES. Secondly, purposive sampling was used to select departments whose employees are more directly involved in AI-enabled work processes. These departments include Op, IT, DB, CS, and HRM. Employees in these departments possess the relevant knowledge and practical experience required to provide reliable information on the study variables. Moreover, simple random sampling was used to select respondents from identified departments. This technique ensured that every eligible employee had an equal chance of being selected, thereby minimising sampling bias and enhancing representativeness of the sample.

Data for this study were obtained from a primary source, using a structured, closed-ended questionnaire. Measured on a five-point Likert scale, ranging from Strongly Agree (5), Agree (4), Undecided (3), Disagree (2), to Strongly Disagree (1). This measurement scale enabled respondents to indicate the extent of their agreement with statements relating to the study variables.

The use of primary data was considered appropriate because it provided firsthand information from employees who actively interact with AI technologies within SB.

Questionnaire was divided into 3 sections. Section A elicited information on respondents' demographic characteristics. Section B contained dimensions of AI-DWD, namely AI-DTA, AI-SDM, and AI-EWR. Section C contained dimensions of ES, namely EcS, EnS. And SoS. Moreover, this study employed face validity and content validity to establish the validity of the questionnaire. Face validity was ensured by presenting draft questionnaire to intellectuals and experts for critical check. Their observations and recommendations regarding clarity, wording, appropriateness, and relevance of questionnaire items were implemented. Content validity was established by ensuring that the questionnaire items adequately covered all the dimensions of the study variables as identified in the conceptual framework and reviewed literature. More so, questionnaire items were adapted from previously validated empirical studies on AI, work design, and enterprise sustainability to ensure that the instrument comprehensively measured the constructs under investigation.

To establish the reliability of questionnaire, a pilot study was conducted involving employees of a commercial bank other than SB to avoid contaminating actual study sample. This enabled researchers to identify ambiguous items and assess consistency of the questionnaire before data collection. Reliability of the instrument was determined using Cronbach's Alpha coefficient, which measures internal consistency of questionnaire items. According to Nunnally and Bernstein (1994), a Cronbach's Alpha value of 0.70 or above indicates acceptable reliability for social science research. After pilot study, questionnaire responses were entered into the Statistical Package for the Social Sciences (SPSS), and Cronbach's Alpha coefficients were computed for each construct and for the overall instrument. Any items found to reduce the reliability coefficient were reviewed before final administration of questionnaire. Consequently, the instrument was considered reliable for collecting data for this study. Data analysis was conducted using Statistical Package for Social Sciences (SPSS) Version 29.

### 3.2 Model specification

For this research, F-S component of MR is adopted as basis of analysis because MR is a relevant model whenever multiple determinants of IV or DV are projected in a study [9].

$Y = f(X)$  Where:  $X = x_1, x_2, x_3$  and  $Y = y_1, y_2, y_3$

$x_1$ = AI-DTA,  $x_2$ = AI-SDM,  $x_3$ = AI-EWR

$y_1$ =EcS,  $y_2$ =EnS,  $y_3$ =SoS

Hence, for joint influence, F-S model is required:

$$F = R^2/k/1 - R^2/n - k - 1$$

Model components

$R^2$ = Coefficient of determination

$n$ = Total sample size (number of observations)

$k$ = Number of independent variables (predictors)

Table 1

Sample Characteristics

| Variable          | Category                   | Frequency | Percentage |
|-------------------|----------------------------|-----------|------------|
| Gender            | Male                       | 169       | 76.0       |
|                   | Female                     | 53        | 24.0       |
| Age               | < 25 years                 | 71        | 32.0       |
|                   | 25–34 years                | 58        | 26.0       |
|                   | 35–44 years                | 31        | 14.0       |
|                   | 45–54 years                | 31        | 14.0       |
|                   | >55 years                  | 31        | 14.0       |
| Marital Status    | Single                     | 71        | 32.0       |
|                   | Married                    | 151       | 68.0       |
| Qualification     | OND/NCE                    | 13        | 6.0        |
|                   | HND/Bachelor's Degree      | 62        | 28.0       |
|                   | Master's Degree            | 53        | 24.0       |
|                   | Professional Qualification | 45        | 20.0       |
|                   | PhD                        | 49        | 22.0       |
| Department        | IT                         | 84        | 38.0       |
|                   | HRM                        | 58        | 26.0       |
|                   | Op                         | 53        | 24.0       |
|                   | DB                         | 22        | 10.0       |
|                   | CS                         | 5         | 2.0        |
| Work Experience   | Not >5 years               | 62        | 28.0       |
|                   | 6–10 years                 | 53        | 24.0       |
|                   | 11–15 years                | 58        | 26.0       |
|                   | 16–20 years                | 31        | 14.0       |
|                   | >20 years                  | 18        | 8.0        |
| Employment Status | Permanent                  | 102       | 46.0       |

|       |          |     |       |
|-------|----------|-----|-------|
|       | Contract | 107 | 48.0  |
|       | Others   | 13  | 6.0   |
| Total |          | 222 | 100.0 |

Source: Field Survey (2026).

Table 1 revealed that 169 respondents (76.0%) were male, while 53 respondents (24.0%) were female, indicating that majority of the respondents were male. With respect to age, 71 respondents (32.0%) were below 25 years, 58 respondents (26.0%) were between 25 and 34 years, while 31 respondents (14.0%) each fell within age categories of 35–44 years, 45–54 years, and 55 years and above. This indicates that respondents from different age groups participated in this study, although younger employees constituted largest proportion.

Regarding marital status, findings showed that 151 respondents (68.0%) were married, whereas 71 respondents (32.0%) were single, suggesting that married persons constituted a greater proportion. Educational qualification of respondents revealed that 13 respondents (6.0%) possessed OND/NCE qualifications, 62 respondents (28.0%) held HND/Bachelor's degrees, 53 respondents (24.0%) possessed Master's degrees, 45 respondents (20.0%) had professional qualifications, and 49 respondents (22.0%) possessed PhD qualifications. This demonstrates that respondents were generally well educated, with majority possessing at least a bachelor's degree or higher, thereby enhancing credibility of information provided. In terms of departmental distribution, 84 respondents (38.0%) were from IT, 58 respondents (26.0%) were from HRM, 53 respondents (24.0%) were from Op, 22 respondents (10.0%) were from DB, while 5 respondent (2.0%) was from CS. Highest representation of employees from IT Department is appropriate considering that AI-DWD is closely associated with technology-based organisational processes.

Moreover, Table 1 indicated that 62 respondents (28.0%) had not greater than five years of working experience, 53 respondents (24.0%) had between 6 and 10 years of experience, 58 respondents (26.0%) had between 11 and 15 years of experience, 31 respondents (14.0%) had between 16 and 20 years of experience, while 18 respondents (8.0%) had more than 20 years of working experience. This distribution suggests that this study captured views of employees with varying levels of organisational experience, thereby providing a balanced perspective on AI-DWD and ES. Finally, employment status of respondents showed that 102 respondents (46.0%) were permanent staff, 107 respondents (48.0%) were contract staff, while 13 respondents (6.0%) belonged to other employment categories. This indicates that both permanent and contract employees were adequately represented in the study. Overall, the socio-demographic profile of the

respondents indicates that this study drew responses from employees with diverse backgrounds. Such diversity enhances representativeness of the sample and provides a comprehensive basis for examining the influence of AI-DWD on enterprise sustainability in SB.

#### 4. Results

##### Response Rate

A total of 222 copies of questionnaire were administered and validly retrieved. This represents a 100% response rate.

Table 2

*Joint Influence of AI-DTA, AI-SDM, and AI-EWR on EcS*

| Model      | Sum of Squares | Df | Mean Square | F       | Sig.  |
|------------|----------------|----|-------------|---------|-------|
| Regression | 10.501         | 3  | 3.500       | 219.299 | 0.000 |
| Residual   | 0.734          | 46 | 0.016       |         |       |
| Total      | 11.235         | 49 |             |         |       |

a. DV: EcS; b. Predictors: (Constant), AI-DTA, AI-SDM and AI-EWR

Source: Authors' calculation using F-S

Table 3 indicates that regression model is statistically significant, with an F-value of 219.299 and a p-value of 0.000, which is less than the 0.05 level of significance ( $F = 219.299, p < 0.05$ ). This implies that AI-DTA, AI-SDM, and AI-EWR demonstrate a statistically significant influence on EcS in SB. Furthermore, it shows that MR is suitable for explaining variations in EcS.

##### Decision on Hypothesis One

Since MR is statistically significant ( $F = 219.299, p = 0.000 < 0.05$ ),  $H_1$  is supported. Therefore, it is sealed that AI-DTA, AI-SDM and AI-EWR jointly demonstrate statistically significant influence on EcS in SB.

Table 3

*Joint Influence of AI-DTA, AI-SDM, and AI-EWR on EnS*

| Model      | Sum of Squares | df | Mean Square | F     | Sig.  |
|------------|----------------|----|-------------|-------|-------|
| Regression | 0.051          | 3  | 0.017       | 0.067 | 0.977 |
| Residual   | 11.690         | 46 | 0.254       |       |       |
| Total      | 11.741         | 49 |             |       |       |

a. DV: EnS; b. Predictors: (Constant), AI-DTA, AI-SDM and AI-EWR

Source: Authors' calculation using SPSS

Results presented in Table 3 reveal that MR is not statistically significant, with an F-value of 0.067 and a p-value of 0.977, which is greater than the 0.05 level of significance ( $F = 0.067$ ,  $p > 0.05$ ). This indicates that AI-DTA, AI-SDM and AI-EWR do not jointly have a statistically significant influence on environmental sustainability in SB.

### Decision on Hypothesis Two

Since the significance value of the regression model ( $p = 0.977$ ) is greater than 0.05 level of significance,  $H_2$  is not supported. Therefore, it is locked that AI-DTA, AI-SDM and AI-EWR do not jointly have a statistically significant influence on environmental sustainability in SB.

Table 4

*Joint Influence of AI-DTA, AI-SDM, and AI-EWR on SoS*

| Model      | Sum of Squares | Df | Mean Square | F       | Sig.  |
|------------|----------------|----|-------------|---------|-------|
| Regression | 10.123         | 3  | 3.374       | 254.461 | 0.000 |
| Residual   | 0.610          | 46 | 0.013       |         |       |
| Total      | 10.733         | 49 |             |         |       |

a. DV: SoS; b. Predictors: (Constant), AI-DTA, AI-SDM and AI-EWR

Source: Authors' calculation using F-S

Results presented in Table 4 indicate that the regression model is statistically significant, with an F-value of 254.461 and a p-value of 0.000, which is less than the 0.05 level of significance ( $F =$

254.461,  $p < 0.05$ ). This implies that AI-DTA, AI-SDM, and AI-EWR, taken together, significantly influence SoS in SB.

### Decision on Hypothesis Three

Since significance value ( $p = 0.000$ ) is less than 0.05 level of significance,  $H_3$  is supported. Therefore, it is resolved that AI-DTA, AI-SDM, and AI-EWR jointly have a statistically significant influence on SoS in SB.

## 5. Discussion

This research has offered empirical insights into the influence of AI-DWD on ES. For instance, following the test of  $H_1$ , existence of a joint influence of AI-DTA, AI-SDM, and AI-EWR on EcS was found. This is in alignment with empirical-based research by [7], whereby it was reported that AI-A enhanced CSP. Though, model used in [7] examined no joint effect of DV on IV. Moreover, findings of this study are similar to those of [14], which found that AI plays a significant role in SuB performance in China. Notwithstanding, template of the study by [14] was not that of joint impact. Moreover, findings of this study agreed with results from the work of [13], which indicated a significantly positive effect of AI on LO and SuB in Turkey. Nevertheless, that study was not designed to verify join effect. Therefore, this study on AI-DWD and ES has not only confirmed some of the earlier studies, but it has also brought clearer insight. Having examined the joint influence of AI-DWD determinants on a determinant of ES, it has addressed methodological and analytical gaps observed in earlier studies.

Findings of this study support earlier findings; for instance, [19] found that AI-enabled investment recovery (AI-IR) does not play a significant mediating role in environmental sustainability. Similarly, [20] reported that AI-A imposes adjustment-related costs. Also, [15] reports that “AI can produce negative outcomes due to increased energy demand, potential for perpetuating bias in decision models, and violation of individual privacy rights.” Likewise, [21] found that ethical issues diminish the relevance of AI on environment. Moreover, [3] reported a negative coefficient of AI in an analysis for environmental sustainability. Besides, [4] found that “AI investment exhibits nonlinear and asymmetric effects on environmental quality in the long run”. As well, economic growth, if not accompanied by eco-friendly practices, can exacerbate ecological deterioration [4]. Furthermore, [2] found that 17% of environmental studies portray AI's impacts as negative.

Findings from the test of H<sub>3</sub> revealed that AI-DTA, AI-SDM, and AI-EWR had a positive and significant joint influence on SoS. This finding is consistent with the proclamation of [17], who found that transformative technologies (TT) have latent to aid organisations to endure on their sustainability trajectory. It is, however observable that [17] explored no joint influence of IV on DV. More so, findings from this research support the argument by [11-13] that AI enhances engagement with stakeholders. Nonetheless, joint influence method of analysis was not adopted in that study. Besides, findings of current study concur with report by [16], who found that relationships within organization has been reformed via the practice of AI. Yet, in that research, joint influence was not conceptualized for any analysis. Also, finding of this work align with those of [8], who argued that digital transformation correlates with employee reskilling and upskilling initiatives. But that research was not structured to test for joint effects. Moreover, findings of this study support findings by [7], who found that AI-driven work design (AI-DWD) promotes SoS. Yet, that study did not test for the joint influence of DV on IV.

## 6. Conclusion

On the basis of results of this research, it is inferred that work design enabled by AI is a vital strategic resource that contemporary organisations, particularly firms in financial sector, are using to enhance enterprise sustainability. With the work of AI embedded in it, businesses can now automate repetitive tasks, assist decision-making at managerial level, and transform workflows to increase efficiency of the organisation and its long-term competitive ability. Nevertheless, the research finds that AI-driven work design is necessary, but not sufficient to enhance environmental sustainability. The non-significant effect observed may imply that environmental sustainability is more dependent on overall organisational effort. In sum, this study concludes that firms that want to be able to sustain their competitive advantage should pursue AI-EWR in the context of a broader organisational transformation strategy and invest in complementary sustainability initiatives.

Based on the findings and conclusions of this study, the following recommendations are made: SB should intensify her practice of adoption of AI-driven task automation across its operational processes to improve efficiency, reduce operational costs, minimize human errors, and enhance economic sustainability. Investment in AI innovations should be accompanied with continuous monitoring to ensure optimal performance and value creation. Policymakers in SB should strengthen the use of AI-supported decision-making systems by integrating advanced

analytics, machine learning, and business intelligence tools into strategic and operational decision-making processes. This will enhance quality, speed, and accuracy of managerial decisions, thereby improving organisational performance and competitiveness. More so, implementation of AI-enabled workflow redesign should be carefully planned and managed. However, since this study found a negative influence of workflow redesign on economic sustainability, management in SB should adopt structured change management strategies, provide adequate employee training, and ensure staff participation during workflow transformation to minimize implementation challenges and resistance to change. In addition, given that AI-driven work design did not significantly influence environmental sustainability. SB's management should complement AI-A with dedicated environmental sustainability initiatives, such as (green practices, energy-efficient technologies, paperless operations, carbon reduction programmes), and environmentally responsible business policies to improve environmental performance.

This study makes several significant contributions. First, this research conceptualises AI-EWR and its effect on the enterprise sustainability to a multi-dimensional level. Contrasting many earlier studies which approached only organisational performance or technology adoption. Clearly, this research projects economic, environmental and social facets of sustainability together under a common conceptual lens. Second, this paper makes an empirical contribution by breaking down AI work design into AI task automation, AI-supported decision-making, and AI-enabled workflow redesign, and thus shows how distinct AI work practices affect different aspects of enterprise sustainability. Third, the study adds to methodological literature through application of MR analyses in exploring joint influences of the dimensions of AI-driven work design on enterprise sustainability. This method provides more compelling evidence than studies that drew largely on bivariate correlations or descriptive analyses. Fourth, this research adds value to those barely existing literature on AI-driven work design inclined organisation in emerging economies with specific focus on SB. Consequently, this study provides empirical insights that could guide managers, policymakers, and scholars who are interested in AI-A and sustainability in the context of developing nations.

Regardless of contributions of this research, some limitations exist. Firstly, this study focused on one company, which may limit applicableness of its results to other firms. Second, this investigation was based on cross-sectional survey data that showed perceptions of respondents at one point in time only. Therefore, trend is missing. Thirdly, the primary means of data collection

in this study was through self-administered questionnaire. Hence, answers rested completely on what employees perceived and their own opinion, which could be subjective and affected by response bias or social desirability bias. Fourthly, this research focused on three aspects of AI-influenced work design and three aspects of enterprise sustainability. Factors related to the organisation, such as leadership style, organisation culture, innovation ability, digital maturity, regulatory compliance and technological infrastructure, were not considered, which may also have certain impact on enterprise sustainability.

In view of limitations of this study, adjoining suggestions are made for future research. Future studies should extend the scope by conducting comparative studies involving multiple firms to enhance the generalisability of findings. More so, intending researchers should employ longitudinal research designs to examine how AI-driven work design influences enterprise sustainability over time and to establish causal relationships more effectively. Furthermore, subsequent research should consider mixed method, possibly examine mediating or moderating roles of variables such as organisational culture, employee digital competence, innovation capability, organisational resilience, or change management in the relationship between AI-driven work design and enterprise sustainability. In addition, future studies should investigate other dimensions of AI-driven work design, such as human–AI collaboration, AI governance, digital leadership, intelligent knowledge management, and AI ethics, to provide a broader understanding of AI-enabled organisational transformation. Moreover, comparative studies between Nigerian organisations and organisations in other African countries or developed economies are also recommended to identify contextual differences in AI-A, work design practices, and enterprise sustainability outcomes.

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