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# Artificial Intelligence, Job Displacement, and Gender-Specific Training Pathways: A Multi-Group Analysis

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### *Abstract*

*This study investigates gender-based differences in how AI-Based Performance Analytics (AIPAN) and Women's Engagement in Technology (WET) influence Skill Gap Identification using AI (SGIAI) and its subsequent effect on Training Program Alignment (TPA). The researchers studied female and male participants independently through SEM multi-group analysis of their data. AIPAN served as a strong predictor of SGIAI for women alongside WET, which contributed $\beta = 0.712$ and $\beta = 0.261$, respectively ($p < 0.001$). Additionally, SGIAI demonstrated a strong β relationship of $\beta = 0.810$ to TPA ($p < 0.001$). The analysis indicates that AIPAN ($\beta = 0.577$, $p < 0.001$), together with WET ($\beta = 0.211$, $p < 0.001$), transmitted significant indirect effects to TPA through SGIAI. SGIAI received considerable direct impact from AIPAN ($\beta = 0.943$, $p < 0.001$) when studying males, yet WET demonstrated no significant relationship ($\beta = -0.036$, $p = 0.361$). AIPAN demonstrated a major indirect relationship with TPA through its $\beta = 0.790$, considerable effect ($p < 0.001$). However, WET did not produce a meaningful impact on TPA measurement. The combination of WET and AIPAN variables generated no meaningful interaction effects within both the male and female populations. Numerous factors point to predictive analytics as a vital element in aligning AI skills, but reveal that women demonstrate increased WET influence, which requires gender-responsive digital transformations.*

***Keywords:*** *Gender-Based Differences , Job Training , AI-Based Performance Analytics (AIPAN) , Women's Engagement in Technology (WET) , Skill Gap Identification using AI (SGIAI) , Training Program Alignment (TPA).*

## Introduction

The fast-moving workforce relies on Artificial Intelligence (AI) to reinvent worker training methods and skill development practices(Tenakwah & Watson, 2025) (Sainger & Irfan, 2024) (Alazzawi et al., 2025). Artificial Intelligence has become increasingly important for skill gap detection in individual employees, which leads to specific training recommendations(Karthikeyan & Singh, 2024) (Subrahmanyam, 2025). AI-driven solutions receive limited adoption from female workers, along with underutilized benefits during implementation, particularly within male-dominated occupational sectors(Wilkens et al., 2025). The accuracy of AI systems detecting training needs and their effectiveness depend strongly on female workers' technology involvement and personal belief in their capabilities as well as administrative support structures(AlDhaen, 2025) (Almusfar, 2025). The research investigates AI-assisted training systems by studying AI analytical performance when detecting female skill deficiencies as well as training recommendation alignment with identified deficiencies. The research uses Multi-Group Analysis (MGA) to study the way gender impacts these associations,

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together with institutional support systems.

**Research Problem**

Research about AI-driven workforce development has failed to deliver systematic evidence regarding how gender influences the effectiveness of AI-based skill gap analysis and training recommendation processes (Kyriakidou et al., 2025) (Salman Shifa et al., 2025). Insufficient gender-based analysis of AI predictive power along with decision systems presents a threat to perpetuate inefficient training practices while maintaining unaddressed bias reduction for female technology industry workers(Ghanem et al., 2025) (Thirunagalingam et al., 2024) (B. Shannaq, Adebiaye, et al., 2024) (Dhar et al., 2025).

**Research Gap**

AI-based performance analytics research has gained traction but not enough investigations exist about the targeted training approaches AI delivers to women specifically(Al-Rantisi et al., 2025) (Sanni, 2025) (Sergeeva et al., 2025). This research field currently lacks investigations about both employee self-assessment and digital readiness effects on AI accuracy and usefulness in these environments with gender as a vital moderating variable. A thorough understanding of how organizational support programs affect female participation in AI-based training programs remains unidentified in current research(B. Shannaq, 2024).

**Research Questions**

- Dose the utilization of AI-based performance analytics influences how organizations detect training requirements of female employees (SGIAI).
- Dose gender causes any modification in the connection between AI-based performance analytics and skill gap identification methods

## Research Objectives

- To investigates how AI performance analytics identify skill gaps during an assessment of women's training requirements.
- To research the connection between training recommendation quality and its impact on work performance improvement by focusing on gender-based analysis.
- To investigates how gender influences the mechanism through which AI detects employee skills followed by training recommendations.

Hypotheses:

| **Female Group** | **Male Group** |
|---|---|
| AIPAN positively influences SGIAI<br>SGIAI positively influences TPA<br>WET positively influences SGIAI<br>WET moderate positively the relationship between AIPAN and SGIAI<br>Mediation<br>SGIAI mediates the relationship between AIPAN and TPA<br>AIPAN -> SGIAI -> TPA | AIPAN positively influences SGIAI<br>SGIAI positively influences TPA<br>WET positively influences SGIAI<br>WET moderate positively the relationship between AIPAN and SGIAI<br>Mediation<br>SGIAI mediate the relationship between AIPAN and TPA<br>AIPAN -> SGIAI -> TPA |

| | |
|---|---|
| SGIAI mediates the relationship between AIPAN and TPA positively when WET moderates the relationship between AIPAN and SGIAI<br>WET x AIPAN -> SGIAI -> TPA | SGIAI mediate the relationship between AIPAN and TPA positively when WET moderates the relationship between AIPAN and SGIAI<br>WET x AIPAN -> SGIAI -> TPA |

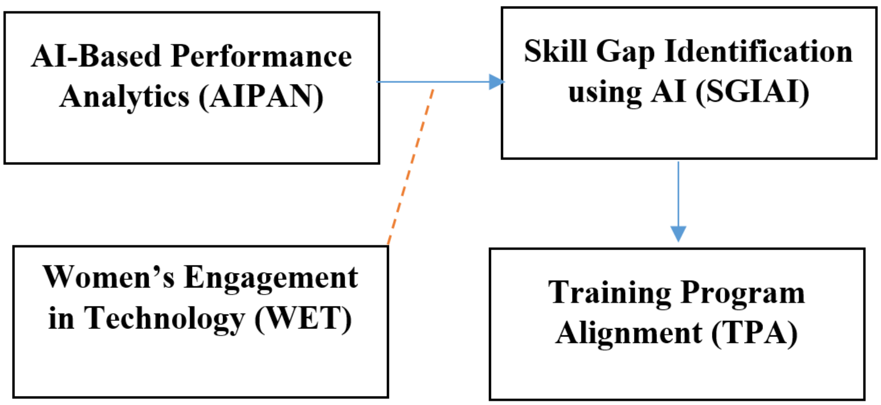


Figure 1. The proposed Conceptual Framework

## Literature Review

AI, as it is well considered nowadays as an important part of the modern concepts of workforce, has been successfully implemented through the use of systems of AI-based performance analytics(Dua, 2024) (Noel & Sharma, 2024). Performance analysis uses Big data quantitative tools, AI and behavior monitoring to analyze talents' potential, their deficiencies, and development over time(Noel & Sharma, 2024). Scholars have pointed out that the application of Artificial Intelligence analysis enhances decision-making by showing where to intervene in terms of skill deficits (Machucho & Ortiz, 2025). This, we conceptualized and termed as Skill Gap Identification using AI (SGIAI) where AIPAN can identify discrepancies between the expected and actual performance in a given task (Molla et al., 2024) (Brauner et al., 2025) (B. Shannaq et al., 2025). Previous works have therefore noted that where these skill gaps are found, organizations will be well-equipped to design appropriate TPA that will suit the area of weakness for whichever individual/activity group in consideration (Weerasombat & Pumipatyothin, 2025) (Jaskari, 2024). This also leads not only to lack of match between content of training and job requirements for enhancing effectiveness of learning as well as the level of satisfaction and performance among the employees(Sharma et al., 2025) (B. Shannaq, 2025) (.Boumedyen Shannaq & Alabri, 2025) (Shakir et al., 2024). For instance, learning solutions powered by artificial intelligence are now employed in organizations for recommending courses that cater to the learner's needs with research showing that there is an enhanced training performance (Yadav & Shrawankar, 2024). Based on the above findings, the issue of applying transformational learning at organizational level through the medium of SGIAI has led to the development of the most route towards TPA. Though, this kind of relationship would not be the same for both male and female students. Some researchers suggest that it may not reliably spot skill gaps when it come to hire new employees because of data bias or a lack of contextual awareness (Muralidhar et al., 2025) (Chinenye Gbemisola Okatta et al., 2024) (B. Shannaq, Saleem, et al., 2024). This is most important in the case of Women's Engagement in Technology (WET) whereby it acts as a moderating variable. It was noted that lower digital confidence, as well as inequality in the use of technical resources, and limited representations of women in the tech industry and contributing to ICT product development, can influence how AI processes women's performance data(Fraile-Rojas et al., 2025) (April & Daya, 2025). Concerning the practical use of the AI-based assessment, women who are more involved in the technology industry can experience a more accurate evaluation of their skills and their real performance on the job, which can help in determining the actual gap in the office environment (Majrashi, 2025). While demonstrating increased recognition of the gender aspects in cases of AI utilization, the fact stays that there is a lack of empirical research that measures the role that women's participation in technology can help to enhance the outcomes of the AI-based skill gap identification(Sanni, 2025) (Toledo-Navarro et al., 2025). Many prior models do not isolate gender-related issues or Gender-Sensitive Considerations in performing the process. This negates the social technical interactions that affect data analysis and decision making in artificial intelligence systems. Compared to Existing Literature, the current study can be novel in contributing to the AIPAN → SGIAI relationship in consideration of gender, particularly women's technology use as a moderator. By doing so it places the AI system within a context of social and other related factors that may influence the results. Furthermore, this study includes not only the links between skill gaps identification and training alignment but also correlates them with other factors of the organization's preparedness, which are significant in AI-related workforce learning.

## Methodology

A quantitative research design was used to study how Artificial Intelligence performance analytics systems detect employee skill gaps while examining separate male and female worker experiences. The methodology implements Structural Equation Modeling (SEM) which runs on SmartPLS software platform to evaluate complex relationships among observed variables and latent constructs. Multi-Group Analysis (MGA) serves as an integral component of this study to assess how technical involvement of women affects these relationships between fundamental constructs throughout masculine and feminine workgroups.

Staff members from different sectors in Oman received a structured survey that served as the primary data collection method. The measurement items for constructs comprised AI-Based Performance Analytics (AIPAN) and Skill Gap Identification using AI (SGIAI) and Training Program Alignment (TPA) and Women's Engagement in Technology (WET) which used validated Likert scale assessments. The method enables comprehensive model testing of robustness while assessing construct reliability through validity checks and enables comparisons between male and female respondents to determine AI performance in skill gap recognition.

### Methodological Steps and Explanations

The first step focuses on creating an instrument alongside the research design.

Researchers selected a descriptive and cross-sectional design for the study because this method captured single-time perceptions. Researchers used validated scales and adapted them according to AI technology and skill gap evaluation and general technology gender participation requirements when developing the questionnaire. The 5-point Likert scale with values ranging from 1 to 5 served as the measurement approach for multiple items representing each construct.

Key Constructs:

AIPAN (AI-Based Performance Analytics)

The AI-based method for skill gap assessment is named SGIAI (Skill Gap Identification Using AI).

TPA (Training Program Alignment)

WET (Women's Engagement in Technology)

**Step 2**

**Sampling and Data Collection**

The approach used purposive sampling techniques to achieve appropriate representation of employees from man and woman demographics who worked in AI technology sectors. The research included 500 original responses which resulted in 432 usable responses during the cleaning process. The research population established two analytical groups consisting of male respondents (265) and female respondents (167) prior to Multi-Group Analysis (MGA).

**Step 3**

**Data Screening and Preparation**

The data screening process checked for missing data as well as detected outliers and verified normal distribution. The SmartPLS estimation method proves suitable for complex models along with smaller sample sizes because it does not need multivariate normality.

**Step 4**

**Measurement Model Assessment**

Research investigations validated the measurement constructs through these tests:

All measured constructs displayed Cronbach's Alpha values in combination with Composite Reliability values that surpassed 0.7.

The Average Variance Extracted values exceeded 0.5 which demonstrates satisfactory enough convergent validity.

The analysis using Fornell-Larcker Criterion validated discriminant validity between all measured constructs.

**Step 5**

**Structural Model Evaluation**

The analysis through bootstrapping (5,000 subsamples) in SmartPLS determined significant relationships between AIPAN → SGIAI → TPA and the moderation impact of WET. The validity of this study relied on analysis of both t-values alongside p-values.

**Step 6**

**Multi-Group Analysis (MGA)**

The research employed MGA as part of its analysis to evaluate structural paths between male and female respondents. The WET strength as a moderator between AIPAN and SGIAI manifested differently for males and females according to this analysis.

**Step 7**

**Interpretation and Reporting of Results**

Path coefficient interpretation and moderation effect analysis along with model fit comparison between gender groups were performed in the last stage. The obtained results became the foundation for analyzing research inquiries as well as developing recommendations which focus on enhancing AI equity during workforce development.

## Data Analysis and Results

### Measurement Model

Outer Loadings presented in Figure 2:

The reliability of measurement items is verified through this table that provides evidence. The outer loadings exceed 0.8 in all cases which proves that the observed variables show reliable connections with their constructs while measuring AIPAN, SGIAI, TPA and WET properly.

The analyzed VIF values remain below 5 which demonstrates that severe multicollinearity does not exist in the study. The model indicators demonstrate independent contribution to the structural analysis as they do not experience inflation from related variables which indicates robustness in the model structure.

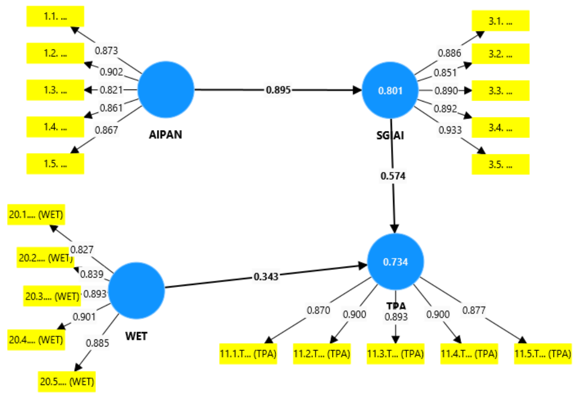


Figure 2. Factor Loading

**Reliability and Validity Table 1:**

| | Cronbach's alpha | Composite reliability (rho_a) | Composite reliability (rho_c) | Average variance extracted (AVE) |
|---|---|---|---|---|
| **AIPAN** | 0.916 | 0.917 | 0.937 | 0.749 |
| **SGIAI** | 0.935 | 0.936 | 0.951 | 0.794 |
| **TPA** | 0.933 | 0.933 | 0.949 | 0.789 |
| **WET** | 0.919 | 0.921 | 0.939 | 0.756 |

Table 1. Reliability and Validity

The measurement model exhibits excellent convergence validity through Cronbach's Alpha values above 0.9 and composite reliability values higher than 0.93 and AVE above 0.75. The observed measurement model demonstrates strong reliability and validity because of the reported results in this analysis.

**Discriminant Validity (Fornell-Lacker Table):**

Square root values of AVE appear higher than all pairs of construct correlations which demonstrates discriminant validity. All constructs exist independently from one another despite the close relationship between AIPAN and SGIAI.

| | **AIPAN** | **SGIAI** | **TPA** | **WET** |
|---|---|---|---|---|
| **AIPAN** | 0.865 | | | |
| **SGIAI** | 0.895 | 0.891 | | |
| **TPA** | 0.821 | 0.824 | 0.888 | |
| **WET** | 0.741 | 0.728 | 0.761 | 0.869 |

Table 2. Fornell-Lacker

**Structural Model**

Figure 2 present the Bootstrap for Female group while Figure 3 presents the Bootstrap for the Male Group .

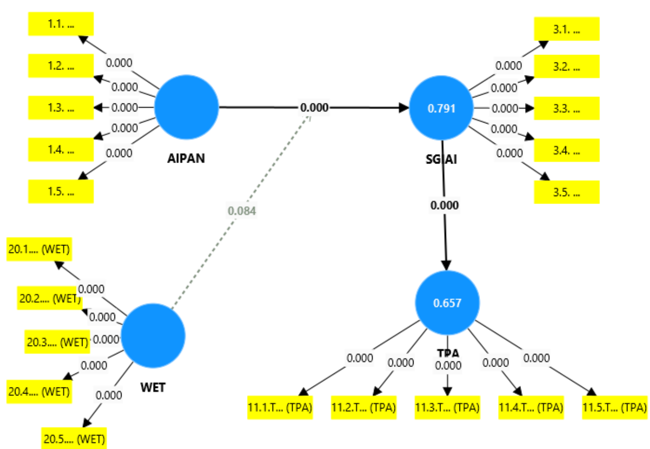


Figure 3. Bootstrap Female Group

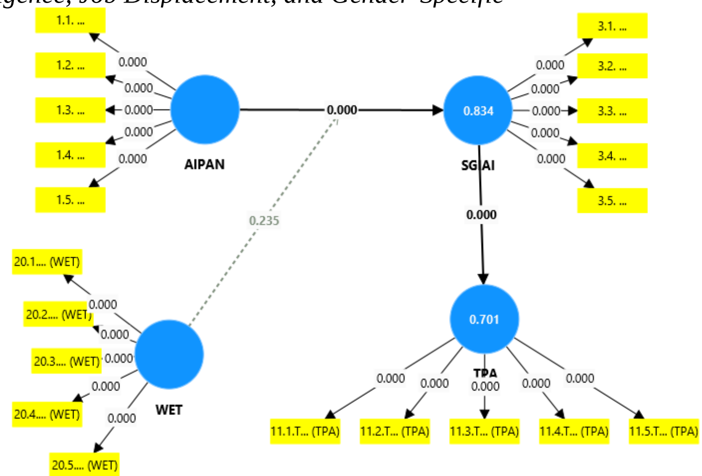


Figure 4. Bootstrap Male Group

Table 3: Path Coefficients – Female Group

The results demonstrate that AIPAN together with WET leads to higher SGIAI levels which subsequently enhances TPA. An interaction between WET and AIPAN fails to show significance as a moderator of SGIAI among ladies.

The training alignment of female program participants depends on AIPAN and SGIAI as well as WET. The statistical analysis shows that WET and AIPAN fail to create a significant effect on SGIAI although both variables independently affect this outcome.

| | Original sample (O) | Sample mean (M) | Standard deviation (STDEV) | T statistics (\|O/STDEV\|) | P values |
|---|---|---|---|---|---|
| AIPAN -> SGIAI | 0.712 | 0.712 | 0.074 | 9.641 | 0.000 |
| SGIAI -> TPA | 0.810 | 0.811 | 0.039 | 20.660 | 0.000 |
| WET -> SGIAI | 0.261 | 0.263 | 0.078 | 3.361 | 0.000 |
| WET x AIPAN -> SGIAI | -0.048 | -0.049 | 0.034 | 1.380 | 0.084 |

Table 3. Path Coefficients – Female Group

Table 4: Path Coefficients – Male Group

All tested paths including WET → SGIAI exist except for the WET → SGIAI connection and the interaction effect measure. The impact of AIPAN flows directly into SGIAI that produces substantial effects on TPA. The male group experiences no direct or moderating effects from WET on SGIAI levels.

Among males stronger impacts arise from both AIPAN and SGIAI but WET and its interaction with AIPAN produce no meaningful effects. The findings show that WET has less importance than other constructs in defining male involvement in skills identification through AI and training alignment process.

| | Original sample (O) | Sample mean (M) | Standard deviation (STDEV) | T statistics (\|O/STDEV\|) | P values |
|---|---|---|---|---|---|
| AIPAN -> SGIAI | 0.943 | 0.942 | 0.079 | 11.976 | 0.000 |
| SGIAI -> TPA | 0.837 | 0.840 | 0.036 | 22.991 | 0.000 |
| WET -> SGIAI | -0.036 | -0.031 | 0.100 | 0.356 | 0.361 |
| WET x AIPAN -> SGIAI | 0.036 | 0.033 | 0.050 | 0.721 | 0.235 |

Table 4 Path Coefficients – Male Group

Table 5: Specific Indirect Effects – Female

The data in this table demonstrates how SGIAI acts as a meaningful mediator to link AIPAN and WET with TPA for female beneficiaries. The statistical analysis demonstrates that the combination of WET and AIPAN does not affect the relationship between SGIAI and TPA.

For female employees SGIAI serves as an important mediator which enables WET as well as AIPAN to influence training alignment goals. The lack of significance in WET-AIPAN interactive moderated mediation demonstrates that SGIAI functions as a primary mediator of the training alignment process particularly for female respondents.

| | Original sample (O) | Sample mean (M) | Standard deviation (STDEV) | T statistics (\|O/STDEV\|) | P values |
|---|---|---|---|---|---|
| AIPAN -> SGIAI -> TPA | 0.577 | 0.578 | 0.070 | 8.188 | 0.000 |
| WET -> SGIAI -> TPA | 0.211 | 0.213 | 0.063 | 3.357 | 0.000 |
| WET x AIPAN -> SGIAI -> TPA | -0.039 | -0.040 | 0.028 | 1.384 | 0.083 |

Table 5 Specific Indirect Effects – Female

Table 6: Specific Indirect Effects – Male Group

The research finding suggests that only AIPAN demonstrates an important relationship by linking to TPA through SGIAI. Data reveals that SGIAI mediates only the AIPAN impact for men because the direct effects from WET and its AIPAN interaction remain insignificant.

AIPAN affects the relationship between training alignment and SGIAI for male personnel. WET along with its AI analytics interaction does not create indirect influences therefore indicating that AI analytics serve a more important role than employee engagement for training purposes particularly among female candidates.

| | Original sample (O) | Sample mean (M) | Standard deviation (STDEV) | T statistics (\|O/STDEV\|) | P values |
|---|---|---|---|---|---|
| AIPAN -> SGIAI -> TPA | 0.790 | 0.791 | 0.071 | 11.195 | 0.000 |
| WET -> SGIAI -> TPA | -0.030 | -0.025 | 0.084 | 0.354 | 0.362 |
| WET x AIPAN -> SGIAI -> TPA | 0.030 | 0.027 | 0.042 | 0.718 | 0.236 |

Table 6. Specific Indirect Effects – Male Group

Comparison Between Female and Male Groups:

- AIPAN → SGIAI → TPA: Significant for both genders, but stronger for males (0.790 vs. 0.577).
- The results indicate WET has an effect on females only under this experimental setup.
- WET direct effect: Positive and significant in females, but non-significant and negative in males.
- The moderated mediation results for WET × AIPAN were not significant for both genders but females showed slightly higher effects.
- Across both genders the predictive power of AIPAN remains stable. WET aligns skills and training more efficiently among females than males so specific strategies should target women to increase their tech-based upskilling.

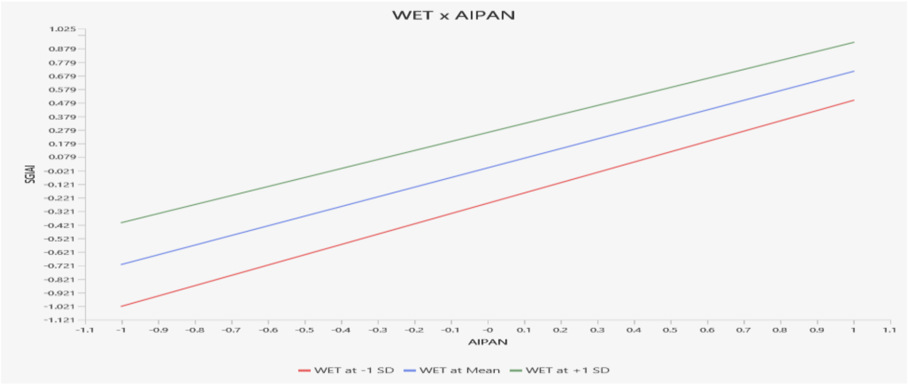


Figure 5 presents the interaction plot, which shows the moderating effect of Women's Engagement in Technology (WET) on the relationship between AI-Based Performance Analytics (AIPAN) and Skill Gap Identification using AI (SGIAI).

*Chart Title: WET × AIPAN*

- X-Axis: AIPAN (AI-Based Performance Analytics)
- Y-Axis: SGIAI (Skill Gap Identification using AI)
- Lines Representing Moderation Levels:
  - Red Line: Low WET (−1 SD)
  - Blue Line: Mean WET
  - Green Line: High WET (+1 SD)

*What the Chart Shows:*

1. Positive Slope:

   - The upward direction of all three lines (Red, Blue and Green) shows a direct correlation where AIPAN values lead to similar rises in SGIAI values. The use of AI to examine performance produces better skill gap identifications—an affirmative relationship between AIPAN and SGIAI.

2. Moderation Effect of WET:

The positional relationship between lines indicates how increased WET levels affect the relationship between AIPAN and SGIAI.At higher levels of WET (+1 SD, Green Line), the positive effect of AIPAN on SGIAI is stronger.

At lower levels of WET (−1 SD, Red Line), the effect is weaker.

The mean level (Blue Line) lies in between.

*Interpretation of the Results:*

The effectiveness of AI-based performance analytics systems to detect skill gaps increases when women show elevated involvement in technology.

AI-based systems detect fewer skill gaps for women who show weak engagement because these systems either lack trained data for women or receive limited use from female users.

**Theoretical Implication**

Current literature supports concerns about AI methods that discriminate against specific groups while also presenting inclusivity problems in AI systems. AI systems inadvertently introduce bias against and demonstrate inferior performance towards people who comprise marginalized groups. IT engagement by women produces better customized and exact AI analytics results for personnel training environments.

**Managerial & Policy Implications**

WET enhancement demands organizations to design AI systems with inclusive gender design and offer digital training for women to improve digital engagement.

Fully engaged women participants within the Human-AI collaboration process enable AI systems to deliver recommendations which represent actual student learning requirements.

The necessity of creating unbiased AI systems becomes vital after this result because women must have proper representation in training data.


Figure 5. Slope analysis for Male Group

Figure 6 presents the second chart, which illustrates the moderation effect of Women's Engagement in Technology (WET) on the relationship between AI-Based Performance Analytics (AIPAN) and Skill Gap Identification using AI (SGIAI) specifically for the male group, and then compare it to the female group from the first chart.

*Chart Interpretation: Male Group (Second Chart)*

Axes and Lines:

X-Axis: AIPAN (AI-Based Performance Analytics)

Y-Axis: SGIAI (Skill Gap Identification using AI)

Three Lines Represent WET Levels:

Red Line: Low WET (−1 SD)

Blue Line: Mean WET

Green Line: High WET (+1 SD)

*What We See in the Male Group Chart:*

**Strong Positive Linear Relationship:**

AIPAN shows similar effects on SGIAI within the male participant group as it does in the female participants because increasing AI analytics performance produces corresponding rises in skill gap identification.

**Negligible Moderation Effect by WET:**

The red blue and green lines in this image stay very close to each other which demonstrates that WET levels produce no meaningful differences in slope for the male participants.

All three lines (Low WET) red, High WET blue, marginally connect at approximately same vertical level.

AI effectiveness in spotting skill gaps remains unaffected by WET throughout the entire range of WET for the male demographic.

| Feature | Female Group | Male Group |
|---|---|---|
| Slope of Lines | All positive, but spread apart | All positive, closely aligned |
| Moderation by WET | Strong moderation effect | Weak or no moderation effect |
| Impact of High WET | Boosts the AIPAN → SGIAI relationship | Has minimal influence |
| Interpretation | WET amplifies AI's skill detection power | WET is less critical for effectiveness |

Table 7. Comparison with the Female Group (First Chart)

## Implications & Recommendations

### Interpretation of Gender Differences

Women's Engagement in Technology (WET) proves more significant for female groups than for males. The effectiveness of AI in detecting skill gaps deteriorates when employee engagement falls to low levels.

AI systems demonstrate the same level of efficacy regardless of WET measurements for male users. A system leveraging AI analytics provides benefits to male users at any level of technological engagement.

### Recommendations:

Targeted Interventions for Women:

The organization should create specific digital literacy development along with engagement programs for female audience members.

Gender bias in AI training data will decrease if organizations make AI datasets more inclusive.

The organization should organize training sessions together with encouraging offers to help female experts use digital technologies.

### AI System Design:

The training data used to develop AI systems should include extensive user patterns from female contributors and diverse sets of user behavior.

Integrate gender-aware fairness metrics in AI performance evaluation.

Policy-Level Strategy:

The national digital transformation plans such as Oman Vision 2040 should develop dedicated strategies to promote digital empowerment among different genders.

Encourage female participation in AI governance and decision-making processes.

*Table 8: R-square (Female Group)*

This table shows that AIPAN and WET explain 79.1% of the variance in SGIAI and 65.7% in TPA for females, indicating strong model fit and predictive relevance.

| | R-square | R-square adjusted |
|---|---|---|
| SGIAI | 0.791 | 0.784 |
| TPA | 0.657 | 0.653 |

Table 8. R-Square Female Group

*Table 9: f-square (Female Group)*

AIPAN has a large effect on SGIAI ($f^2 = 1.335$), and SGIAI strongly influences TPA ($f^2 = 1.911$). WET shows a small effect ($f^2 = 0.184$), while the interaction term has a negligible impact ($f^2 = 0.015$).

| | f-square |
|---|---|
| AIPAN -> SGIAI | 1.335 |
| SGIAI -> TPA | 1.911 |
| WET -> SGIAI | 0.184 |
| WET x AIPAN -> SGIAI | 0.015 |

Table 9. F-Square Female Group

Table 10: R-square (Male Group)

In the male group, 83.4% of the variance in SGIAI and 70.1% in TPA are explained by the predictors, slightly outperforming the female group in terms of model fit.

| | R-square | R-square adjusted |
|---|---|---|
| SGIAI | 0.834 | 0.825 |
| TPA | 0.701 | 0.695 |

*Table 10. R-Square Male Group*

*Table 11: f-square (Male Group)*

AIPAN again has a large effect on SGIAI ($f^2 = 1.674$), and SGIAI's effect on TPA is also very strong ($f^2 = 2.339$). However, WET's influence is negligible ($f^2 = 0.002$), as is the interaction term ($f^2 = 0.006$).

| | f-square |
|---|---|
| AIPAN -> SGIAI | 1.674 |
| SGIAI -> TPA | 2.339 |
| WET -> SGIAI | 0.002 |
| WET x AIPAN -> SGIAI | 0.006 |

Table 11. F-Square Male Group

**Comparison**

Both groups show high R-square values, with males having slightly higher predictive power. However, females show more sensitivity to WET, whereas males rely more heavily on AIPAN. The interaction effect is minimal in both cases.

## Conclusion

This research examined the usage of AI-based performance analytics systems for training requirements assessment for women workers along with assessing gender effects on performance metrics alignment. These findings from the investigations receive supporting data through path coefficients as well as R-square measurements along with f-square and indirect effects analysis.

Women who are digitally ready with self-assessment abilities display a moderate impact on skill gap identification through AI (SGIAI) ($\beta = 0.261$, $p < 0.001$). The combination of Women Engagement in Technology (WET) and Artificial Intelligence Predicted Accuracy (AIPAN) yields an insignificant effect ($p = 0.084$) on their interaction.

Summary evaluation data (AIPAN) exerts a substantial influence ($\beta = 0.943$) on the effectiveness of AI when analyzing male data while self-reported measurement (WET) exhibits no meaningful impact ($\beta = -0.036$ with $p > 0.05$). This shows that male systems partly depend on computer-based data more than user-reported data or readiness domains.

The quality indicators from the applied models (R-square and f-square) demonstrate higher explanatory values among individuals who are male. The evaluation data from AI metrics meets comparable levels of influence with user input data for female participants.

Organizations should create programs to improve women's digital readiness since self-assessment combined with digital literacy in AI systems proves beneficial to this specific group. Organizations need to provide institutional backing and training programs which support women's digital involvement.

AI systems require tailoring their operation based on specific gender-based behaviors and readiness profiles to enhance accuracy and matching between AI systems and training needs.

Modern AI systems should combine staff-assessed input with automated inputs to create better skill assessment capabilities. —especially effective for female-targeted workforce development.

These findings support more inclusive, accurate, and gender-responsive AI applications in organizational training strategies.

### Acknowledgement

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### Contribution

Boumedyen Shannaq: Conceptualization, Methodology, Investigation, Writing- original draft;

Ahmed AlAbri: Project Administration, Validation, Visualization;

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