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AI-Driven Training, Employee Skill Development and Employee Outcomes: Evidence from Public-Sector Energy Sector

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Abstract

It's not very clear how AI-based training (AIDT) improves employee outcomes and under what organizational conditions. The current study looked into the relationship between AIDT and decision-making capability (DMC), performance enhancement (PE), and work productivity (WP) among employees of public sector electricity distribution companies (DISCOs) in Pakistan, including employee skill development (ESD) as a mediator and organizational culture (OC) as a moderator. Partial least squares structural equation modelling (PLS-SEM) was used to analyze survey data from 423 respondents, with three parallel models based only on different outcome variables. The measurement quality was good (HTMT ≤ 0.44; item loadings 0.74-0.83). Bootstrapped results show a positive relationship between AIDT and ESD (β = 0.22, p < 0.001), and ESD in turn is related to DMC (β = 0.27), WP (β = 0.26), and PE (β = 0.20). AIDT also has a direct effect on WP (β = 0.22) and PE (β = 0.10); there is no direct effect on DMC (β = 0.09, p = 0.082), which suggests that skills fully mediate the effect on DMC and partially mediate it for WP and PE. ESD is significantly related to each outcome from OC (β = 0.28; 0.18-0.33, respectively), while the interaction of AIDT × OC is not significant in any model. The models explain 14% of the variance in ESD and 17-22% in the outcomes. These results indicate that AI-driven training has positive direct effects on outcomes and promotes the development of skills, and a supportive culture positively affects the outcomes, but it doesn't change the strength of the training effect. The results provide a basis for HR managers and policymakers in the power sector to plan AI-powered training.

Keywords: AI-driven training; employee skill development; organizational culture; decision-making capability; work productivity; performance improvement; electricity distribution; Pakistan; PLS-SEM

Introduction

The use of Artificial Intelligence (AI) in organizations is affecting the way they manage their people. AI is changing people management in organizations. Machine learning, predictive analytics, and intelligent tutoring systems in HRM now provide customized learning paths, appropriate training, and instant feedback (Dwivedi et al., 2021). The ability to identify skill gaps and customize content for each employee has been linked to higher engagement and proficiency.

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AI-based training (AIDT) is emerging as an important way to develop workforce skills, and AI is changing work processes, decision-making, and performance (Alasmri & Basahel, 2022; Morandini et al., 2023).

These benefits don't come just from technology. New skills like critical thinking, problem-solving, data analysis, and lifelong learning are necessary when working with AI, and the impact of AI depends on the context in which it's used (Jarrahi et al., 2023). Training and development also give employees a chance to enhance their skills, which helps improve work performance and retention. This basically focuses on the connection between AI-driven training and employee outcomes through employee skills. Still, whether these skills actually translate the effects of AI-driven training into better productivity, decisions, and performance is rarely tested.

This issue is arising in Pakistan's public sector electricity distribution companies (DISCOs). In this sector, operational inefficiency is due to a lack of skills and outdated training methods, along with a slow adoption of new technology (Abdullah et al., 2023). This problem is further worsened by a rigid, hierarchical system and resistance to change (Abdullah et al., 2023; Patrick & Khattak, 2025). Although these organizations have the potential to train their employees on a large scale through AI-driven training, there is very little evidence that they actually do so or how they do it.

This creates three gaps that need to be filled. First, research on AI in HRM is still limited (Prikshat et al., 2023), which means there's a need for more advanced training in HRM with AI and a clearer strategic plan for HR managers. Experimental evidence studying the effects of AI-based training on key employee outcomes is also limited. Second, we don't know much about this path. According to human capital theory, investing in training is expected to enhance skills and, as a result, increase productivity (Becker, 1964; Schultz, 1961), and learning methods have been identified as a mediating factor between training investment and innovation (Sung & Choi, 2014). In the case of AI-driven training, the mediating role of skill development is not yet well established. Thirdly, the environment of the institution can also be important. A positive educational environment enhances the impact of training, while a strict or bureaucratic culture can hinder the learning process (Murire, 2024), and the relationship between culture and AI integration is not yet fully understood. Therefore, there is no practical evidence that culture affects the impact of AI-based training, so this question remains open.

This study aims to fill these gaps by exploring how AI-based training affects the productivity, decision-making ability, and performance of employees in Pakistan's public sector DISCO companies, using employee skill development as a mediator and organizational culture as a moderating factor. It asks these three questions:

- RQ1. Does using AI in training affect employees' skills, productivity, decision-making, and performance?
- RQ2. Are there benefits of AI-assisted training for both?
- RQ3. Does organizational culture affect how AI training impacts skill development and outcomes?

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To estimate these three parallel models, we use survey data from 423 MEPCO participants and apply partial least squares structural equation modelling (PLS-SEM) to make direct comparisons between the three models easier.

There are four ways of studying, in which this plays an important role. It looks at how skill development is a means of how AI-based training works. It identifies organizational culture as a factor that interferes with both the training-skills relationship and the training-outcomes relationship. It provides a comparison of three employee outcomes within the same framework. And it's an environment that has been less researched, especially in relation to public utilities in a developing country. The results guide HR managers and policymakers in the power industry on where their efforts in AI-based training will pay off and what kind of organizational environment is needed for its success. The rest of the paper presents a literature review (Section 2), development of hypotheses, data, and methodology explanation (Section 3), results (Section 4), discussion of the results (Section 5), and implications (Section 6).

Literature review and hypothesis development

This section provides an overview of theories used in the model, the constructs of the model, and the hypotheses. Figure 1 shows the conceptual framework.

Theoretical foundations

It can't be said why AI-driven training will lead to better employee results and when it won't; there is no universal theory for this. That's why we use four parallel angles that highlight different aspects of the model (Table 1).

Human capital theory: Human capital theory, which is equivalent to a company's idea of investing in its employees, argues that people can also invest in themselves through education, training, skills, knowledge, and health, just like companies, and this investment increases productivity and income (Becker, 1964; Schultz, 1961). According to this theory, AI-based training is an investment in people: it enhances their knowledge and skills, increases their value to the organization, and the benefits of training keep growing. This theory is used to support the basic chain of the model, meaning training is used to build skills, skills are used to boost productivity, and productivity improves the quality and performance of decision-making. But it doesn't say when this investment pays off, so other perspectives are needed.

Social cognitive theory. Social cognitive theory explains how learning happens. It sees learning as an interactive process involving internal factors like self-confidence and motivation, behavior, and environment, while also viewing observational learning, skill experiences, and feedback as sources of self-confidence (Bandura et al., 1999; Bandura & McClelland, 1977). AI training platforms can provide these elements: virtual mentors and simulations as models, flexible systems that adjust task complexity according to the learner's level, and real-time analytics for feedback. Staff who complete such tasks will build both competence and confidence in working with AI in their profession, helping them make better decisions and give feedback. The environment also plays a role, since the encouragement to learn and try new tools will depend on organizational culture and psychological safety (Edmondson, 1999). This theory links to organizational culture.

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Technology acceptance models. According to the Technology Acceptance Model (TAM) Davis (1989); Venkatesh & Bala (2008), a person's attitude toward a technology is linked not just to how useful they perceive it to be, but also to how easy they think it is to use, and both of these ultimately relate to the actual use of the technology. The Unified Theory of Acceptance and Use of Technology (UTAUT) reorganizes these beliefs into performance expectancy and effort expectancy, includes social influence and facilitating conditions, and considers moderators like age, gender, experience, and voluntariness of use (Venkatesh et al., 2003). For AI-assisted training, these theories suggest that the precondition for learning from an AI platform is that the employee accepts and uses it. This is especially important for electricity distribution companies (EDCs), where resistance to technology and limited technical skills, along with rigid structures, are often reported (Abdullah et al., 2023; Patrick & Khattak, 2025). These concepts were not tested in this study, but they were used to explain the differences in the effects of training on employees and the environment. Adopting social influence and facilitating conditions also aligns with the characteristics of organizational culture.

Contingency theory. Contingency theory says that there isn't a single right or wrong way to organize or manage, for an intervention to succeed, it has to fit with internal and external factors, including culture, technology, leadership, and uncertainty (Fiedler, 1964; Lawrence & Lorsch, 1967). This theory can be applied to AI-driven innovation and learning training, which suggests it's not one-size-fits-all and its impact isn't linear: a culture that promotes innovation and learning will boost the training's effect, while a rigid culture will suppress it. That's why organizational culture is considered a moderator.

Table 1. Theoretical lenses and their role in the model

Theory	Element of the model	Hypotheses	Rationale
Human capital theory (Becker, 1964; Schultz, 1961)	AIDT → ESD; ESD → outcomes; mediation	H1, H5-H7, H12	Training is an investment that builds skills, and skills raise productivity, judgment and performance.
Social cognitive theory (Bandura et al., 1999; Bandura & McClelland, 1977)	AIDT → ESD; ESD → DMC; role of the environment	H1, H6, H12	Observational learning, mastery experiences and feedback build self-efficacy and the cognitive skills that support decisions.
TAM and UTAUT (Davis, 1989; Venkatesh et al., 2003)	Background to AIDT → ESD and AIDT → outcomes	H1-H4	Acceptance (usefulness, ease of use, social influence, facilitating conditions) is a precondition for learning from AI platforms; not measured here.
Contingency theory (Fiedler, 1964; Lawrence & Lorsch, 1967)	OC moderating AIDT → ESD and AIDT → outcomes	H8-H11	The effect of training depends on fit with context: supportive cultures amplify it and rigid cultures dampen it.

Note. AIDT = AI-driven training; ESD = employee skill development; OC = organizational culture; DMC = decision-making capability.

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Key constructs

AI-based training (AIDT) is training that uses machine learning, natural language processing, and adaptive learning technologies to personalize content, provide instant feedback, and track progress. It can include AI learning management systems, role-play simulations, and more. It has the ability to provide targeted upskilling according to the skill gaps of each employee, while the challenges include data privacy, transparency in algorithmic skill gaps, and bias issues. The skills needed to work with AI are divided into technical, analytical, and cognitive skills, as well as soft skills like adaptability and problem-solving (ESD) (Morandini et al., 2023). Strategically, it reduces competency gaps in aligned competency development. Organizational culture (OC) is the shared beliefs, values, and principles that shape how members behave. Organizations with a learning culture see new technology as an opportunity for growth rather than a threat (Williamson et al., 2016).

The results of three employees have been examined. Work productivity (WP) can be described as the employees' performance and effectiveness, indicating how well they are meeting organizational goals (Tangen, 2005). Decision-making capability (DMC) refers to making fast and accurate decisions using insights gained from AI (Neiroukh et al., 2024; Tambe et al., 2019). The improvement in employees' effectiveness, performance, and output due to their skills, training, and technology (Alghizzawi et al., 2025; Tambe et al., 2019) is called performance improvement (PE). These three are connected but different: productivity is about output per unit of labor; decision-making capability is about the quality of the decisions; and performance improvement is about the overall change in work performance.

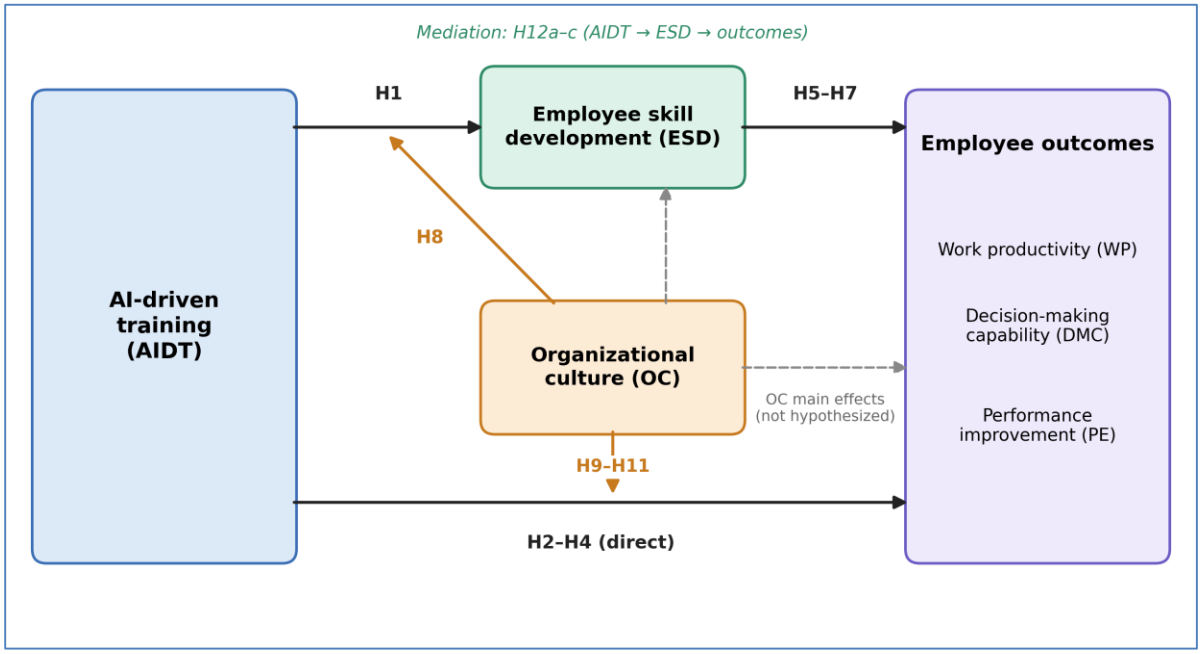


Figure 1. Conceptual framework and hypotheses

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Hypothesis development

AI enabled training and staff development

AI-powered platforms can recognize gaps, customize learning modules, and provide instant feedback, all of which together offer an effective way to learn a skill compared to traditional classroom training. Research has also shown that AI-based practice improves skill acquisition and retention, even if students put in minimal effort (Lira et al., 2026). Other reviews of AI work highlight that both upskilling and reskilling are necessary, whether in technical areas (like data analysis) or soft skills (like adaptability and problem-solving) (Morandini et al., 2023). Both human capital theory and social cognitive theory suggest that mastery experiences, like adaptive practice, simulated tasks, and instant feedback, are linked to skill building and boosting self-confidence. So we speculate:

H1: AI-driven training has a positive impact on employee skill development.

Employee skill development and employee outcomes

Within the framework of the human capital theory, the immediate factor that boosts productivity is skills, and this is exactly what AI evidence shows. Continuous learning becomes possible through AI systems, which help staff acquire the skills that increase their productivity (Bastani et al., 2025; Freeman, 2025; Katona & Gyonyoru, 2025). Other studies on training conclude that it enhances workers' skills so they can handle complex tasks, adapt to new work environments, and improve job performance. AI-based guidance, problem-solving, and training through simulations and scenarios help tackle problems and improve decision-making; AI can assist in making quick decisions based on data (Bondac et al., 2026; Steyvers & Kumar, 2024). However, it’s the employees who can use such analytics, provided they have the analytical skills to understand it. Social cognitive theory also suggests that decision-making ability is based on perception and self-confidence, and skill development will support it. Therefore, we propose this hypothesis:

H2: Employee skill development positively affects work productivity.

H3: Employee skill development enhances decision-making capability.

H4: Employee skill development positively affects performance improvement.

Direct effects of AI-driven training on employee outcomes

AI can also have a direct impact on training outcomes. AI automates prediction tasks, which saves employees time for decision-making and focusing on creative skills, thus complementing human capabilities to reduce skill obsolescence (Hemphill, 2019). AI tools can provide data-driven insights and scenario-based practice that can help enhance decision-making abilities (Alasmri & Basahel, 2022; Davenport & Ronanki, 2018; Stone et al., 2015).

However, many of these studies point to a mediating process. Based on evidence from training research, learning practices influence the outcomes of training investments (Sung & Choi, 2014). If skill development is the main pathway, the effect of training through the skills route may be

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smaller. Analysing both direct and mediating pathways gives us the chance to distinguish between full mediation and partial mediation. So, we propose this hypothesis:

H5: AI-driven training positively affects work productivity.

H6: AI-driven training improves decision-making capability.

H7: AI-driven training positively affects performance improvement.

The mediating role of employee skill development

Looking at it together, H1 and H5-H7 suggest that the relationship between training and outcomes comes through skills. This chain is predicted according to human capital theory because training is a valuable resource that enhances skills. Therefore, we propose the following hypothesis: skill development plays a mediating role in testing the purpose of the study.

H8: Employee skill development mediates the effect of AI-driven training on work productivity (a), decision-making capability (b) and performance improvement (c).

The moderating role of organizational culture

AI-based training is unlikely to affect every organization in exactly the same way. A learning culture tends to embrace new technology more willingly and uses AI training as an opportunity for development (Schein, 2010). An open culture can help reduce technophobia and increase managers' intention to use generative AI (Zhao et al., 2025), and it’s said that culture impacts AI integration effects on employee behavior and performance. Organizations that are open to change are more likely to succeed in digital initiatives, and cultural change in training with AI is a common barrier. Cultural barriers, resistance to change, and lack of HR skills have been identified as key challenges for implementing AI in HRM in Pakistan (Patrick & Khattak, 2025). Based on contingency theory, the takeaway is clear: training will be more effective in cultures that allow learning and innovation, and less effective in rigid, hierarchical cultures.

This evidence is either hypothetical or related to the intentions of authorities, and only a few studies actually examine the impact of culture on the outcomes of employee training. Culture can influence every stage of the process, training can enhance skills but doesn't necessarily translate into productivity, training can help with decision-making, but not necessarily with performance. That's why we propose this assumption:

H9: Organizational culture moderates the relationship between AI-driven training and employee skill development.

H10: Organizational culture moderates the relationship between AI-driven training and work productivity.

H11: Organizational culture moderates the relationship between AI-driven training and decision-making capability.

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H12: Organizational culture moderates the relationship between AI-driven training and performance improvement.

Just like in all moderation testing, organizational culture is also part of every model, directly predicting skill development and also directly predicting outcomes. These main effects are reported as 'extra results' and are not predicted.

Research gap

If we look at everything together, all the literature points out that the skills learned through AI lead to results, and this depends on culture. There are three limitations remaining. First, most research on AI use in HRM is technical in nature or focuses on the intention to adopt it; most studies are conceptual, and there is little direct evidence regarding employee outcomes (Tambe et al., 2019). Second, only a few studies have looked at skill development as a mediating role and organizational culture as a moderating factor within the same model. Third, the evidence on public services is limited, even though there is a strong need to work on these organizations to improve service delivery, practical performance, and compliance with regulations, especially in Pakistan's energy sector. This study addresses these limitations.

Methodology

Context and data

The current research will be based on Multan Electric Power Company (MEPCO), which is a government-sector electricity distribution company in Pakistan. Unfortunately, due to limited resources, data was collected only from this company. A semi-structured questionnaire was used for the research, and purposive (criteria-based) sampling was adopted to collect the data. Employees who had 14 years of formal education (a bachelor's degree or higher) were contacted so that they could better understand and respond to questions about AI-based training. A total of 600 eligible employees were contacted between April 1 and April 30, 2026, and 423 usable responses were received, resulting in a response rate of 70.5%. The details of the participants are shown in Section 4.1. This study was conducted with a distribution company and employees who have at least 14 years of education, and further research should also be conducted with other distribution companies and different employees to confirm the results of this study.

This setting was chosen because the core of the issue is in Section 1. Discos are registered public sector companies whose electricity distribution contracts are based on regulatory loss targets, and their employees' skills and decision-making directly affect their operating performance, while training methods and adoption of technology have been reported as weak. This combination means that training, skills, and outcomes are important for policy but quite unclear. The questionnaire was used because skill development, decision-making ability, and perceived productivity are individual-level concepts and are not available in administrative data. The drawback of this option is that it produces perceptions rather than audited performance indicators, which is addressed in Section 6. The unit of analysis is the individual employee, and all concepts are measured simultaneously from the same respondents.

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Measures

All constructive elements were assessed using multi-item reflective scales with five-point Likert responses. Seven items (AIDT1-AIDT7) were used to measure AI-driven training, eight items (ESD1-ESD8) were used to measure employees' skill development, seven items (OC1-OC7) were used to measure organizational culture, five items (DMC1-DMC5) were used to measure decision-making capability, six items (PE1-PE6) were used to measure performance improvement, and five items (WP1-WP5) were used to measure work productivity. The interaction between AIDT and OC was created as a product term.

Table 1. Measurement constructs, number of items and sources

Construct	Items	Source (item codes)
AIDT	7	Bibi et al. (2025): AIDT1, 6, 7; Sarfaraz & Saeed (2026): AIDT1-5; Badghish & Soomro (2024): AIDT3; Choung et al. (2023): AIDT4
ESD	8	Badghish & Soomro (2024): ESD1, 3, 7, 8; Sarfaraz & Saeed (2026): ESD1, 2, 3, 6, 7, 8; Bibi et al. (2025): ESD2, 4, 5, 6
WP	5	Choung et al. (2023): WP1, 4; Bibi et al. (2025): WP 2, 3, 4, 5
DMC	5	Sarfaraz & Saeed (2026): DMC1-5
PE	6	Choung et al. (2023): PE1; Sarfaraz & Saeed (2026): PE1, 4, 6; Bibi et al. (2025): PE4, 5, 6; Sarfaraz & Saeed (2026): PE2, 3
OC	7	Bibi et al. (2025): OC1, 3; Sarfaraz & Saeed (2026): OC2, 3, 4, 5, 6, 7

Reflective scales with multiple items were used because each concept represents a latent ability or idea that shows up through several indicators. Each concept reduces measurement error that would be expected if estimated with just one item, and the quality of measurement for each item can be checked through its loadings, which isn't possible with a single item. The concepts are clearly linked to assumptions: AIDT represents training input; ESD represents the way training is expected to operate; OC represents the condition that can strengthen or weaken ESD; DMC represents the outcome of training; PE represents the outcome of training; WP represents the outcome of training. The results remain separate and haven’t been combined into a single performance index because training can affect decisions, overall performance, and output in different ways, and a comprehensive index could hide these differences. The interaction between AIDT and OC was included so that the effect of training can vary depending on the cultural level of the participants, and it is included as a direct predictor in each model to ensure that the effect of OC isn’t confounded with its interaction with AIDT.

Analytical strategy

PLS-SEM was chosen for the following reasons: the model includes an interaction term, it is a complex model, and it is designed to explain the variance of the outcomes. Three models were developed. For ESD, the predictors are AIDT or AIDT × OC, and for an outcome (DMC, PE, or WP), both AIDT and ESD were used. The models then only differ in the outcomes, allowing direct comparison in terms of coefficients. The measurement model was evaluated using item loadings and the Heterotrait-Monotrait ratio (HTMT) to test discriminant validity. For assessing the structural model, path coefficients, bootstrapped 95% confidence intervals (CIs), and the

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coefficient of determination (R^2) were used. Bootstrapping: 5,000 and run in R. In the figures and tables, * denotes $p < 0.05$ and *** denotes $p < 0.001$.

The choice of PLS-SEM is based on the recommendation that the method can explain the variability in results when multiple constructs are involved, or there are mediators or interaction terms (Hair et al., 2019). It generally does not assume normally distributed data, which can be useful for Likert-type survey items that are usually skewed. Three parallel models were estimated, one for each outcome, to ensure that the predictor models are consistent and to make sure that any differences in the estimated coefficients are solely due to the outcome (as required for the comparison in Section 4.4). The two modeling concepts presented here (DMC, PE, and WP) are conceptually and empirically different (Section 4), and outcome-specific effects can be directly interpreted.

The measurement model was found suitable for conventional standards. For item loadings, values of 0.70 or higher indicate that a construct explains half or more of an item's variance, and for determining discriminant validity, conservative 0.85 and lenient 0.90 were chosen as the criteria, as recommended by Henseler et al. (2015) to assess overlap between constructs more reliably than older standards. In PLS-SEM, the distribution of samples for path estimates is unknown, so bootstrapped confidence intervals were used in the structural model. If an interval does not include zero and the sign is as predicted, the hypothesis is accepted. The indirect effect was considered as an indirect effect through ESD, and the significance of the direct effect was not examined, with the type of mediation determined based on whether the direct effect is significant or not (Zhao et al., 2010). Standard coefficients have been provided because the paths are measured in different ways so that comparison is possible, and R^2 values are given to show how much of the outcome is explained by the model. The coefficients are standardized and classify relationships, but they don't show them in financial or time units.

Results

Respondent profile

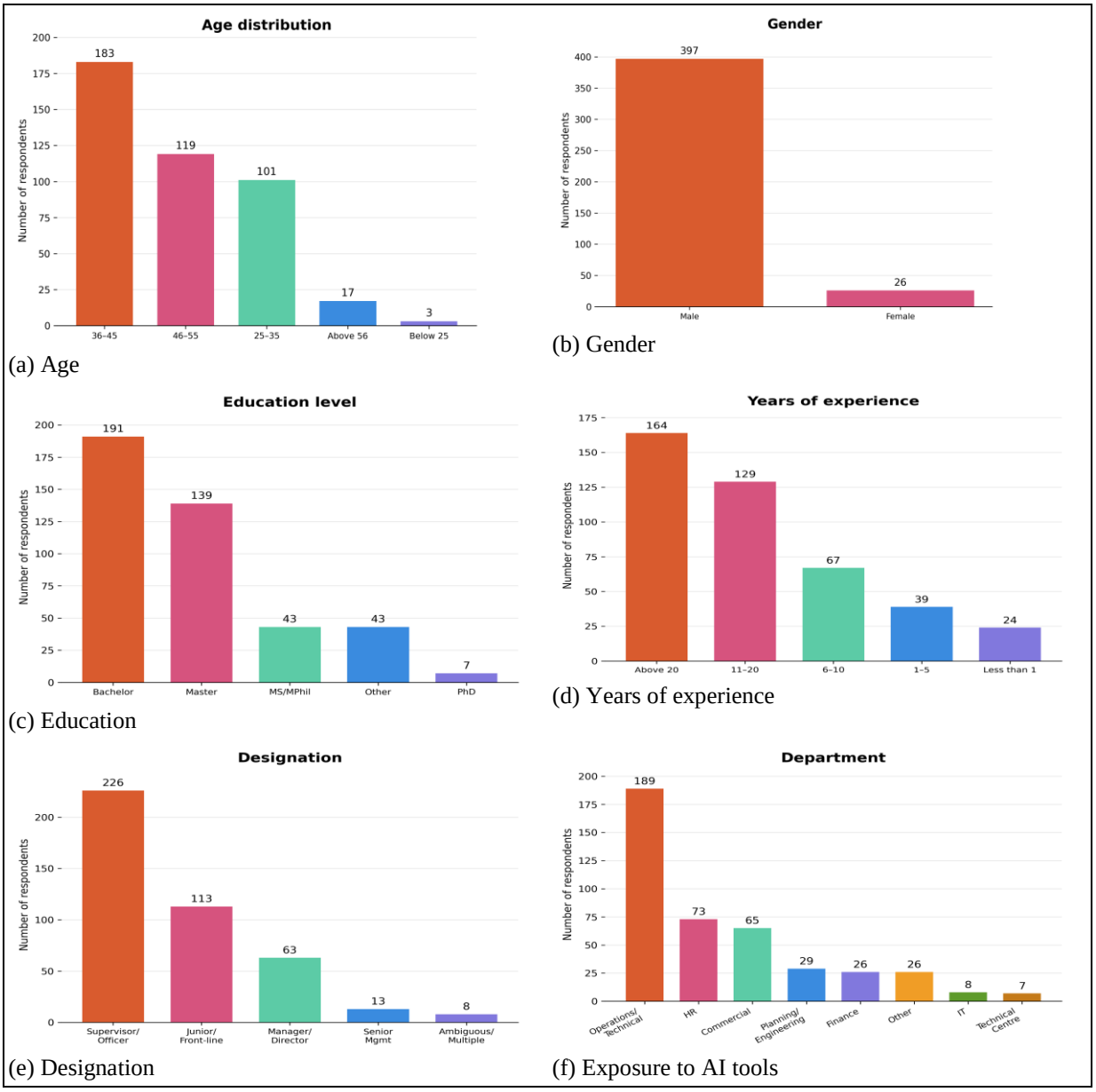
A summary of the sample data is given in Figure 2. Most participants were aged 36-45 years (183; 43.3%), followed by 46-55 years (119; 28.1%) and 25-35 years (101; 23.9%). Men made up 93.9% of the sample (397 participants) and women 6.1% (26), so the results mostly reflect male employment. About 45% of participants had a bachelor's degree (191), 10% had an MS/MPhil (43), a third had a master's degree (139), and 7 had a PhD. Most of our participants were supervisors and officers (226; 53.4%), followed by junior and frontline staff (113; 26.7%), managers and directors (63; 14.9%), and senior managers (13; 3.1%). Experience was substantial, with 164 (38.8%) having more than 20 years of work and 129 (30.5%) having 11-20 years. About half were working in operations or technical departments (189; 44.7%), and nearly a third in HR departments (73; 17.3%) and commercial departments (65; 15.4%).

Measurement model

The item loadings are presented in Figure 3 and Table 2. In all three models, all items load between 0.74 and 0.83, which is above the 0.70 guideline (Hair et al., 2019), and the loading of each

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construct is nearly the same across the models (AIDT 0.74-0.80; ESD 0.75-0.83; OC 0.77-0.83; DMC 0.77-0.83; PE 0.76-0.82; WP 0.79-0.83). Internal consistency is very high (Cronbach's alpha range: 0.87-0.91; composite reliability, ρC: 0.90-0.93; and ρA: 0.87-0.92 for all constructs) and the average variance extracted (AVE) is 0.59-0.67, which is above the 0.50 threshold, indicating that each construct explains more than 50% of the variance in its items. Since the AIDT × OC interaction is a single-indicator product construct, the reliability statistics for this interaction are not meaningful.



(a) Age

(b) Gender

(c) Education

(d) Years of experience

(e) Designation

(f) Exposure to AI tools

Figure 2. Respondent profile (N = 423): (a) age, (b) gender, (c) education, (d) years of experience, (e) designation and (f) department.

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Table 2. Range of standardized item loadings by construct and model

Construct	Items	DMC model	PE model	WP model
AIDT	7	0.74-0.80	0.74-0.80	0.74-0.80
ESD	8	0.76-0.82	0.75-0.83	0.75-0.82
OC	7	0.77-0.82	0.77-0.83	0.77-0.83
Outcome (DMC / PE / WP)	5 / 6 / 5	0.77-0.83	0.76-0.82	0.79-0.83

Note. Values are the minimum and maximum standardized loadings shown in Figure 3; the interaction term is a single-indicator construct and is not shown.

The validity of discrimination was tested using HTMT (Figure 4 and Table 3). All values are comfortably below 0.85 (Henseler et al., 2015). They vary meaningfully between constructs from 0.12 (AIDT-OC) to 0.44 (OC-PE), and the three results are distinct from each other (0.38-0.43). The interaction term is clearly different from all other constructs (0.04-0.07). The upper limits of the bootstrapped HTMT confidence intervals are 0.22-0.53, so the discriminant validity is supported. Since the inner model VIFs are all below 1.17 and the full collinearity VIFs are between 1.13 and 1.37, there is no multicollinearity issue, which is below the 3.3 threshold used to indicate potential bias in the PLS method (Kock, 2015).

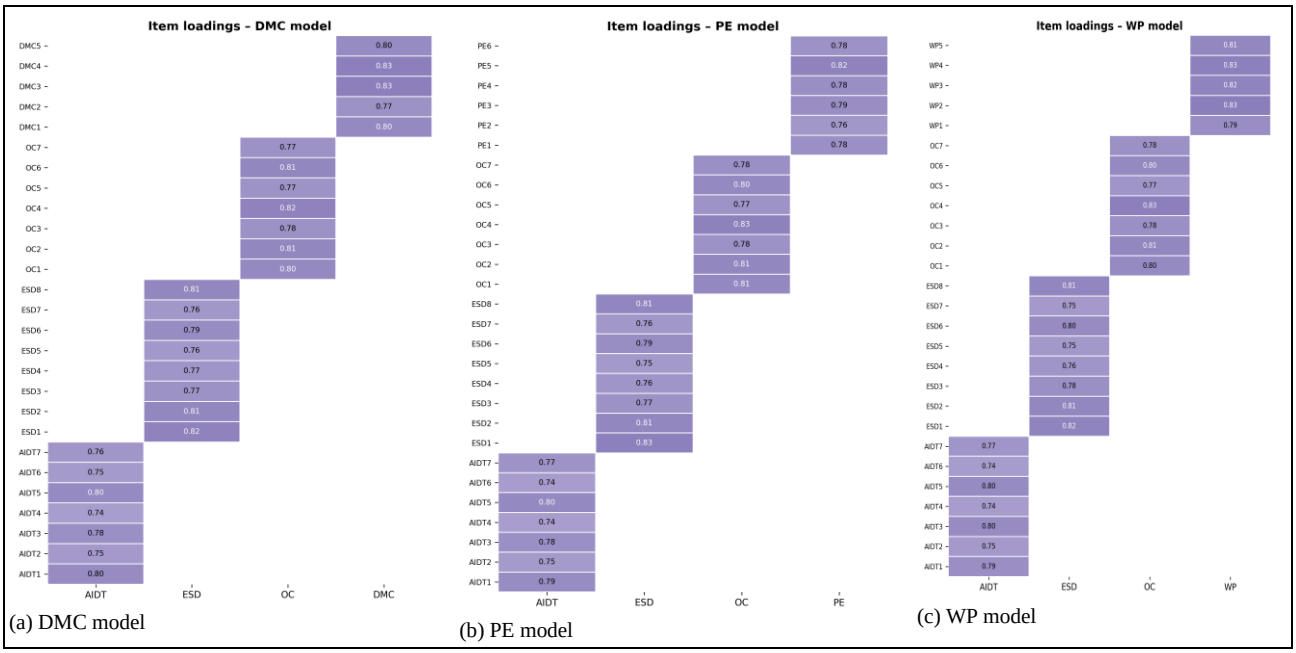
The results of these measurements confirm that the structural coefficients that were read are correct. The amounts of the coefficients given below are not due to few measurements or overlap between structural elements, because they are reliable and the items are not very large. A common method difference is possible since all structural elements come from the same respondents and instrument, but the full collinearity VIFs indicate that this is not a big issue.

Table 3. HTMT values by model

Construct pair	DMC model	PE model	WP model
AIDT, ESD	0.270	0.270	0.270
AIDT, OC	0.121	0.121	0.121
ESD, OC	0.333	0.333	0.333
Outcome, AIDT	0.191	0.205	0.342
Outcome, ESD	0.398	0.355	0.412
Outcome, OC	0.328	0.442	0.317
AIDT×OC, AIDT	0.059	0.060	0.060
AIDT×OC, ESD	0.053	0.052	0.053
AIDT×OC, OC	0.045	0.046	0.043
Outcome, AIDT×OC	0.063	0.053	0.061

Note. Values are taken from Figure 4. “Outcome” is DMC, PE or WP according to the model.

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(a) DMC model (b) PE model (c) WP model

Figure 3. Standardized item loadings for the (a) DMC, (b) PE and (c) WP models. Darker cells indicate higher loadings.

Structural model

The bootstrapped path coefficients and their 95% confidence intervals are shown in Figures 5-7 and compiled in Table 4. The acquisition of ESD is roughly the same across the three models; the difference between outcome acquisitions is due to ESD, which is an important finding. Effect sizes (f^2) are evaluated based on the standards of 0.02 (small effect), 0.15 (medium effect), and 0.35 (large effect) (Lachenbruch & Cohen, 1989).

Training and skill development through Artificial Intelligence (AI) (H1). AIDT is positively associated with ESD across all three models ($\beta = 0.22$; $p < 0.001$; 95% CI approximately [0.14, 0.31]). H1 is supported. The effect size is relatively small: AIDT contributes to a slight increase in skills ($f^2 = 0.06$).

Skill development and outcomes (H5-H7). ESD has positive and significant effects on all three outcomes: DMC ($\beta = 0.27$, CI [0.18, 0.37]), WP ($\beta = 0.26$, CI [0.18, 0.35]), and PE ($\beta = 0.20$, CI [0.11, 0.28]). H5, H6, and H7 are supported. The effects are roughly the same for DMC and WP, and a bit smaller for PE ($f^2 = 0.08$, 0.08, and 0.04).

The direct impact of training with the help of AI (H2-H4). The direct path from AIDT to WP is positive and significant ($\beta = 0.22$, CI [0.14, 0.31]), and the path to PE is also positive ($\beta = 0.10$, CI [0.01, 0.19], $p = 0.025$), so H2 and H4 are supported. The direct path to DMC is positive but not significant ($\beta = 0.09$, CI [-0.01, 0.18], $p = 0.082$), so H3 is not supported. The direct effect of AIDT on WP was the highest ($f^2 = 0.06$), while the direct effect of AIDT on DMC and PE was very small ($f^2 = 0.01$).

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Mixing (H8-H11). The interaction of AIDT × OC is not significant for ESD (β = 0.02-0.03, p = 0.52-0.57, CI [-0.06, 0.12]; H8) or for WP (β = -0.07, p = 0.107; H9), DMC (β = 0.00, p = 0.96; H10) or PE (β = 0.00, p = 0.98; H11). The effect sizes of all interactions are < 0.01. There is no support for any of the four mixing hypotheses: OC does not influence how training aided by AI translates into skills or outcomes.

Table 4. Bootstrapped path coefficients (β) with 95% confidence intervals

Path	DMC model	PE model	WP model
AIDT → ESD	0.22*** [0.14, 0.31]	0.22*** [0.14, 0.31]	0.22*** [0.13, 0.30]
OC → ESD	0.28*** [0.20, 0.37]	0.28*** [0.20, 0.37]	0.28*** [0.20, 0.37]
AIDT×OC → ESD	0.03 [-0.06, 0.11]	0.02 [-0.06, 0.11]	0.03 [-0.06, 0.12]
ESD → outcome	0.27*** [0.18, 0.37]	0.20*** [0.11, 0.28]	0.26*** [0.18, 0.35]
OC → outcome	0.20*** [0.11, 0.30]	0.33*** [0.24, 0.42]	0.18*** [0.09, 0.27]
AIDT → outcome (direct)	0.09 [-0.01, 0.18]	0.10* [0.01, 0.19]	0.22*** [0.14, 0.31]
AIDT×OC → outcome	0.00 [-0.10, 0.10]	0.00 [-0.09, 0.10]	-0.07 [-0.16, 0.02]

Note. * p < 0.05; *** p < 0.001. Values are from the bootstrapped PLS-SEM output; R^2 values are shown in Figure 8.

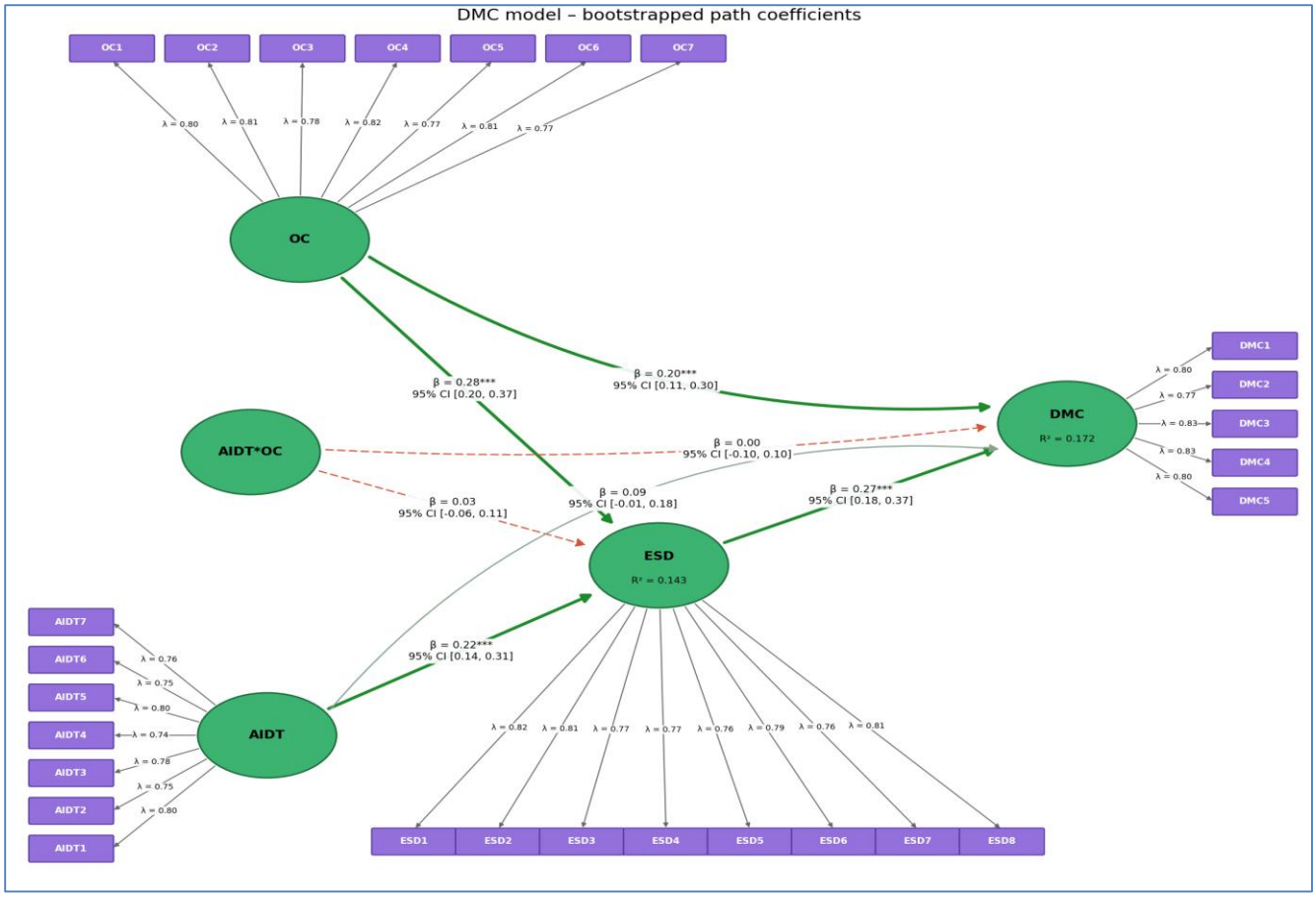


Figure 5. Bootstrapped path coefficients: DMC model. λ = item loading; β = path coefficient with 95% confidence interval.

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Including OC in every model was a straightforward prediction, as is usually the case when testing moderation. It has a positive and significant effect on ESD (β = 0.28, CI [0.20, 0.37], f^2 = 0.09) and on all other outcomes too: DMC (β = 0.20, CI [0.11, 0.30]), PE (β = 0.33, CI [0.24, 0.42]), and WP (β = 0.18, CI [0.09, 0.27]). The most important single pathway in the models is the effect on PE (f^2= 0.12). Exposure to training in AI is associated with 0.22 standard deviations higher in one skill, in standardized terms, and 0.20 to 0.27 standard deviations higher across the outcomes. There are then two ways through which the training influences results. One is through a skill, and for each outcome, this is small (indirect effects range from 0.04 to 0.06 as shown in Table 5). The second one is direct, and it varies depending on the results: it's big for productivity (0.22), smaller for improving performance (0.10), and not significant for decision-making (0.09). When it comes to real-world applications, using AI for training in this data is mainly linked to a general increase in productivity, while using it for decision-making is only beneficial when it enhances skills. These are the pre-established relationships taken from perception data, which just rank the channels but don't tell their financial value.

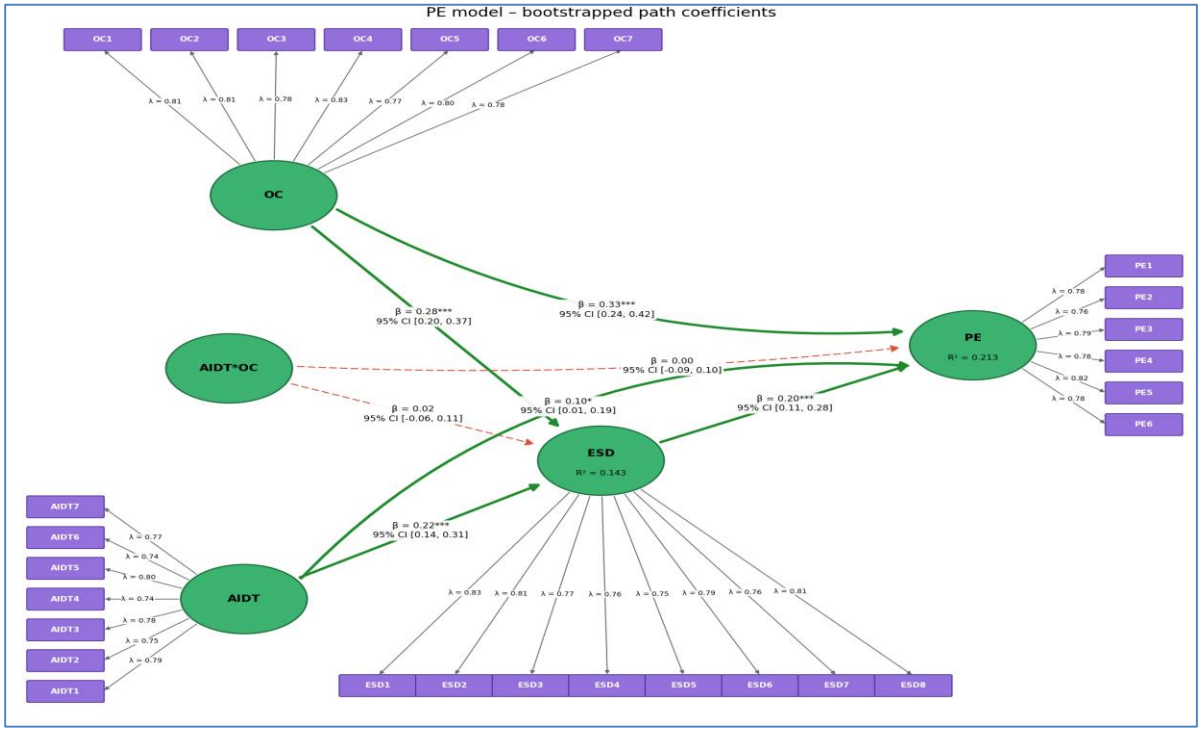


Figure 6. Bootstrapped path coefficients: DMC model. λ = item loading; β = path coefficient with 95% confidence interval.

Table 5. Indirect and total effects (products and sums of reported coefficients)

Effect	DMC model	PE model	WP model
AIDT → ESD → outcome (indirect)	0.060 [0.031, 0.094]	0.043 [0.020, 0.073]	0.057 [0.032, 0.091]
AIDT → outcome (direct)	0.086 [-0.011, 0.184]	0.104 [0.015, 0.195]	0.222 [0.139, 0.308]
AIDT total effect	0.145 [0.052, 0.243]	0.147 [0.058, 0.239]	0.279 [0.202, 0.368]
OC → ESD → outcome (indirect)	0.078 [0.045, 0.116]	0.056 [0.028, 0.088]	0.075 [0.046, 0.112]

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OC → outcome (direct)	0.200 [0.108, 0.295]	0.325 [0.239, 0.416]	0.182 [0.088, 0.271]
OC total effect	0.277 [0.191, 0.367]	0.381 [0.300, 0.464]	0.256 [0.169, 0.344]

Note. Indirect effects are products of the path estimates in Table 4 and total effects are direct plus indirect effects. 95% percentile confidence intervals for indirect and total effects come from 5,000 bootstrap resamples; direct-effect intervals are from Table 4.

Organizational culture is not like a random factor; it's a separate input. It has a stronger direct relationship with performance improvement (0.33) than skills do (0.20), and it relates to decision-making (0.20) and productivity (0.18) in a similar way as skills do (0.27 and 0.26). There's no change in any of these according to the level of training, because H8-H11 were not supported. So, the benefits gained from training and those gained from culture seem to be additive, not complementary: one benefit doesn't depend on the level of the other, and it's possible to plan and budget for both separately.

Comparison across the three models

Figure 8 compares the explanatory power of the models. For ESD, R^2 is 0.14 across all three models, and for DMC it's 0.17, for PE it's 0.21, and for WP it's 0.22. These are modest values and represent a general level of the model based on one institution's behavior, showing that 78-86% of the variation in skills and outcomes is due to factors outside the model.

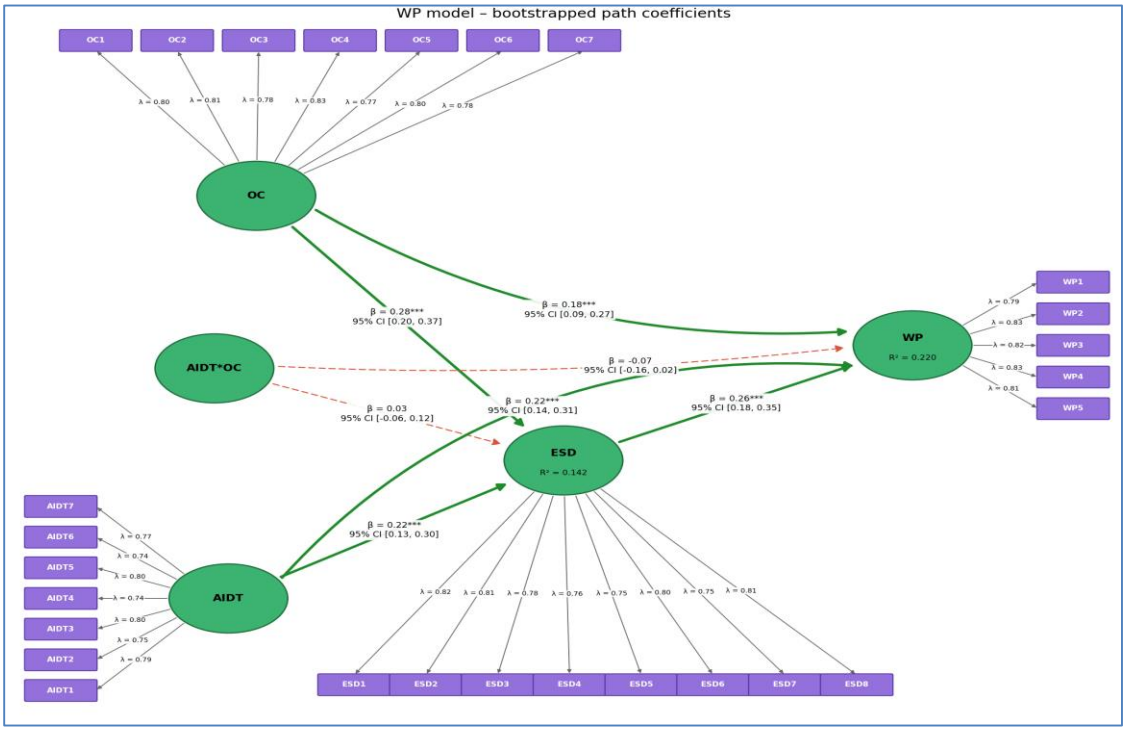


Figure 5. Bootstrapped path coefficients: DMC model. λ = item loading; β = path coefficient with 95% confidence interval.

Figure 9 shows the standard effects used to compare the effects of each outcome. There are three key points here. First, AIDT has a direct effect on WP (0.22) and PE (0.10) but not on DMC (0.09).

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Second, the importance of ESD is almost the same for DMC and WP (0.27 and 0.26) and lower for PE (0.20). Third, the most important predictor for PE is OC (0.33), and it has equal importance for predicting DMC and WP as skills do.

The comparison also shows where an extra unit of effort can have the most impact, as shown in Table 5 based on the overall effect. In terms of productivity, training has a bigger effect (total effect 0.28) while culture has a total effect of 0.26. For decision-making, the overall relationship of culture is higher (0.15 > 0.28), and for improving performance too, culture's relationship is higher (0.15 > 0.38). A manager who is deciding between training programs and culture initiatives can expect different benefits depending on the goal. The coefficients can't be converted into rupee benefits since no cost data was collected; so, to compare cost-effectiveness, cost information would be needed.

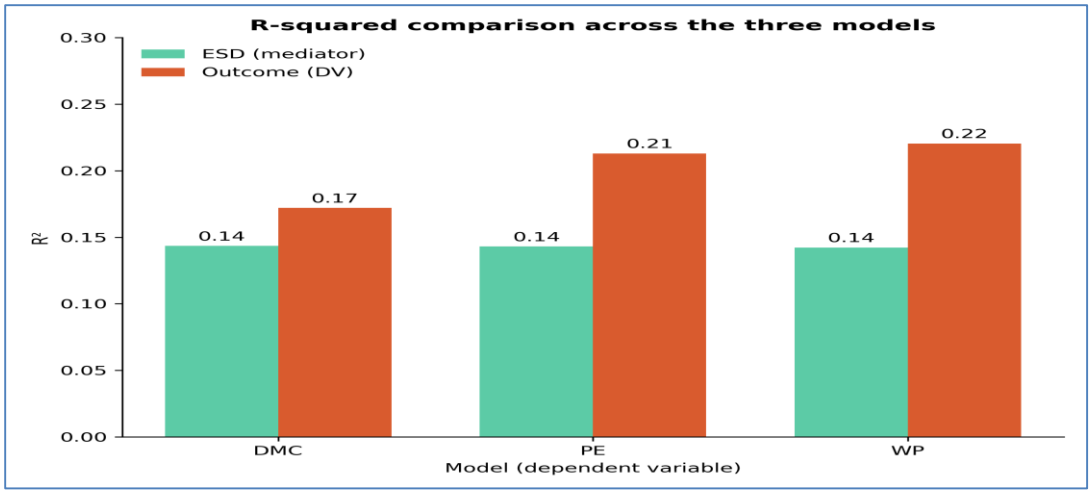


Figure 8. R^2 of the mediator (ESD) and of the outcome in the three models.

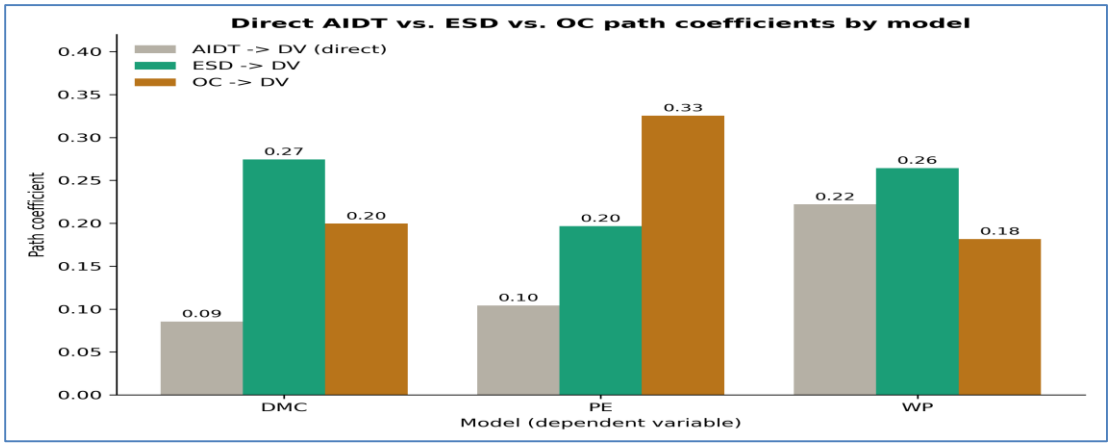


Figure 9. Direct path coefficients from AIDT, ESD and OC to the outcome in each model.

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Mediation through skill development

The indirect and total effects are shown in Table 5, along with the 5,000 bootstrap confidence intervals. The indirect effect of AIDT via ESD is significant in all three models: 0.060 (95% CI [0.031, 0.094]) for DMC, 0.043 ([0.020, 0.073]) for PE, and 0.057 ([0.032, 0.091]) for WP. The direct effect depends on the type of mediation. For DMC, the direct effect is not significant, meaning it's just indirect mediation: the effect of training directly goes to decision-making ability; this is because the effect of training is only mediated through skills (purely indirect mediation). In the case of PE and WP, the direct effect is also strong but with an opposite sign to the mediation effect: complementary (partial) mediation: skills mediate part of the effect while the rest is direct (Zhao et al., 2010). As a result, the following types of cells are supported: H12a-c. The indirect path accounts for 41% of the total effect of AIDT on DMC, 29% on PE, and 20% on WP. Skills are also important in the path from culture to outcomes (0.047 for DMC, 0.028 for PE, and 0.035 for WP), so some of the relationship between culture and outcomes passes through skills.

The indirect effect is the product of two pairs: for DMC it's 0.218 × 0.274 = 0.060, for PE it's 0.218 × 0.197 = 0.043, and for WP it's 0.216 × 0.264 = 0.057. The first pair is small; the mediated effect is also small even if the second pair is medium-sized; and finally, the first pair goes into the direct effect for WP and PE, meaning skill formation is only a small part of the total effect. The practical takeaway for organizations is that skill development is an important pathway, but it's not the only one: productivity and performance can also increase without measurable changes in skills, for instance through AI tools helping with tasks, which hasn't been measured.

Table 6. Hypothesis testing summary

Hypothesis	Statement	Decision
H1	AIDT → ESD (+)	Supported (β = 0.22***)
H2	AIDT → WP (direct, +)	Supported (β = 0.22***)
H3	AIDT → DMC (direct, +)	Not supported (β = 0.09, p = 0.082)
H4	AIDT → PE (direct, +)	Supported (β = 0.10*)
H5	ESD → WP (+)	Supported (β = 0.26***)
H6	ESD → DMC (+)	Supported (β = 0.27***)
H7	ESD → PE (+)	Supported (β = 0.20***)
H8	OC moderates AIDT → ESD	Not supported (β = 0.02 to 0.03)
H9	OC moderates AIDT → WP	Not supported (β = -0.07)
H10	OC moderates AIDT → DMC	Not supported (β = 0.00)
H11	OC moderates AIDT → PE	Not supported (β = 0.00)
H12	ESD mediates AIDT → WP, DMC, PE	Supported (complementary for WP and PE; indirect-only for DMC)

Note. Decisions are based on the bootstrapped 95% confidence intervals in Table 4. H12 was added to test mediation formally. OC main effects were not hypothesized.

The pattern from 4.3 to 4.5 is generally the same as what human capital theory suggests, except for this addition. Training is an investment that pays off based on the skills acquired (Becker, 1964; Schultz, 1961), and research on training shows that the learning process is a means to achieve the investment effects of training (Sung & Choi, 2014). These are the main AIDT-ESD result

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pathways, and that's the logic. Evidence is also found at the company level: (Konings & Vanormelingen, 2015) showed that the productivity benefit from a trained worker is much higher than the wage benefit, indicating that companies can gain productivity benefits from training. The current findings include that some benefits depend on skill development (decision-making) and some manifest directly (productivity and performance) for AI-based training.

The linear relationship between AIDT and productivity matches research on the use of AI in the workplace. Brynjolfsson et al. (2025) found that AI can, on average, increase the productivity of customer support employees by 15%, with the greatest benefit going to less experienced workers, and they also found that the tool helps employees learn. Research by Noy & Zhang (2023) showed that ChatGPT reduced the time required for professional writing tasks by 40% and improved the quality of writing by 18%. Both studies focus on the use of AI tools during work and pay attention to actual results rather than hypothetical training programs or processed outcomes, thus reinforcing productivity trends rather than its limits. This aligns with the idea that decisions should be made based on skills rather than experience, as Hemphill (2019) noted that AI reduces the cost of prediction and increases the value of human decision-making.

Productivity training is the most responsive because it's closest to how people work on a daily basis, the more productive someone is in their work, the more productive they'll be in using AI tools as well, even if other areas of their life aren't particularly measured for improvement. Sharing information, managerial processes, and shared values have a big impact on these decisions and overall performance, which is why culture should get more attention than anything else. This explanation is an interpretation and hasn't been directly tested.

These results are relevant for a public sector distributor with a limited budget. The training budget can be linked to productivity and performance, and it can only be linked to decision-making if it focuses on skill development; training programs should include hands-on practice, guidance, and follow-up; and improvements in skills should be monitored as an intermediate indicator. Culture-related work connects to every outcome, with the strongest link to performance improvement, and it doesn't depend on the training schedule. From this study, which doesn't include any cost, loss, or objective performance data, it's not possible to say whether these relationships lead to lower loss or cost.

There are three precautions for each reading mentioned above. The R^2 values (0.14-0.22) indicate that most of the variations are unexplained, which means the relationships are small and one shouldn't expect a huge impact from any specific program. There are several confidence intervals that are quite large compared to the estimates (for example, the CI for the direct effect on DMC is [-0.01, 0.18]), so you can't be sure about the ranking among nearby paths. The data is also cross-sectional and self-reported, which means the path from training to skills and then to outcomes is theory-based, not design-based.

Discussion

The key finding is that AI-based training is positively linked to employees' skills as well as productivity and performance, whether indirectly (through skills) or directly. The AI training (ADT) path (H1) and all ESD paths for outcomes (H5-H7) are significant, as is the path from ADT

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to PE (H2), but not the direct path to DMC (H3). For this reason, the mediation is complementary for job performance and only indirect for DMC. This aligns with the human capital theory that the benefits of training come from skill enhancement and also provides evidence that there is a learning process between training and its outcomes (Sung & Choi, 2014). It also shows that skills are not the only factor: productivity and performance are linked to AI-based training even when skills are taken into account. This pattern aligns with social cognitive theory, which highlights that the most important elements are skill experience and self-confidence for training to turn into competence, although this was not measured directly.

How strong this mechanism is depending on what is being achieved. The only visible path to decision-making ability is through skills, where training doesn't have a direct specific impact, and 41% of its total effect goes through ESD. This reasonably explains that training can only be developed by using those analytical skills, and therefore, their assessment can't be done through data. The direct effect ($\beta = 0.22$), which is the clearer path, is much higher than the effect through skills ($\beta = 0.06$), probably because productivity depends on how quickly and accurately employees perform their daily tasks with AI assistance. The direct effect on performance is small (0.10), while culture is a strong predictor (0.33), which matches the idea that overall performance mostly relies on shared principles, information sharing, and management processes rather than individual performance.

Organizational culture was found as a standalone factor, not as a moderator. It plays a clear role in skill development and every outcome, but the four moderator hypotheses (H8-H11) were not supported, the interaction coefficients are close to zero and effect sizes are < 0.01. This contradicts contingency theory and the idea that supportive cultures make training more effective, while bureaucratic cultures make it less so (Zhao et al., 2025). This aligns with research findings showing that culture/organizational learning has a direct relationship with outcomes without moderation by training or technology (Amjad et al., 2024; Jamil et al., 2025). Most current research on culture and AI is theoretical and/or related to AI adoption intentions, which might not translate into how AI is actually used to moderate training effects. There could be several possibilities for them: the public sector DISCOs might have a similar hierarchical structure, and the culture might not be that different; or the interaction could be smaller compared to the simple one; or culture could matter in other ways, like through opportunities to apply new skills. The absence of a significant interaction doesn't mean that moderation isn't there; the WP interaction interval [-0.16, 0.02] is consistent with a small negative effect.

The results address the problem that led to this study. In a field where there is a lack of expertise, an outdated training model, and slow adoption of technology, they believe AI training is beneficial, not only as a means to help improve staff productivity and performance, but also as a way to enhance skills, and importantly, its usefulness in decision-making depends on whether skills can improve. They should be seen as relationships, not as evidence that AI training reduces harm, as mentioned in Section 1.

In the end, the R^2 values (0.14-0.22) are relatively low, which is common for attitude models based on surveys from a single organization. This shows that the combination of different written points explains only a small part of the differences in skills and outcomes, meaning the importance of these relationships shouldn't be exaggerated. Despite good reliability and discriminatory accuracy

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(Section 4.2), the moderate explanatory power is due not to measurement issues but to the limited scope of the model.

Conclusion

This work shows that a person can use three parallel PLS-SEM models to conclude that AI training positively impacts employees' skill development, improves work productivity, enhances performance among DISCO employees, and positively affects decision-making ability only through skills. Organizational culture is directly related to skills and all outcomes, especially performance improvement, and does not influence the level of training effect. The takeaway for organizations is that training and culture are two separate levers with different benefits, and skills are the channel that takes training to decision-making.

The effect sizes aren't very large, but there is a pattern in the estimates. AIDT is related to ESD ($\beta = 0.22$), and ESD is related to the outcomes (0.27 for DMC, 0.26 for WP, and 0.20 for PE). Training also directly affects WP (0.22) and PE (0.10), while no significant effect was found on DMC (0.09). The indirect effects through skills are 0.06, 0.04, and 0.06, which account for 41%, 29%, and 20% of the total effects for DMC, PE, and WP, respectively. Culture has direct effects of 0.20 (DMC), 0.33 (PE), and 0.18 (WP), with total effects of 0.28, 0.38, and 0.26. The models explain 14% of the variance in ESD and 17-22% of the variance in outcomes.

These results are not limited to the sample alone. They suggest that AI-assisted training is beneficial in two ways, either it relates to productivity and performance, or it serves as a method of skill-building, and what seems to stand out is skill-building, so training budgets should be estimated based on results and acquired skills. Culture is not necessary for training to have an impact but serves as a source of additional benefits, so investing in culture alongside training is recommended. This is especially good for utility companies that have staff issues and limited budgets, in which case programs that include access to AI tools, practice, and follow-up are better. This study provides evidence at the employee level of a public sector power distribution company in Pakistan, where there was previously a lack of evidence for testing intervention and moderation simultaneously across three similar models.

The results show that there are relationships between self-reported feedback in a country and sector, and they highlight the lack of evidence for measurable reductions in losses or increases in productivity as a result of training; these are mostly based on samples of male supervisors and officers. Future work should use longer-term or experimental designs, objective measures of production and losses, cost data to measure profit, and samples from multiple discos and other utilities. Research that actually quantifies what has been learned, and whether culture affects work units rather than just individuals, will show whether the relationships found here hold up with strong evidence or not.

For DISCO management and HR. Investment in AI-based training can be justified based on productivity and performance, but programs aimed at better decision-making should be designed as skill development: where there’s a training time budget, there should also be a budget for mentoring and follow-up, and skill improvement should be measured. For culture, since OC is directly linked to all outcomes and most connected to performance improvement, investing in

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learning and collaborative processes is valuable, even if a training roadmap or AI skill requirement isn't prioritized. If productivity is the goal, then training comes first, then culture; if better decisions or performance improvement is the goal, culture is at least as important. For policy. For regulators, ministries, and disco boards encouraging the adoption of AI, it's more effective to fund the assessment of organizational practices and workforce training and skills than to just fund AI technology itself.

There are several limitations to note. The data is cross-sectional and self-reported, so it's based on theory rather than causal inference, and the bias from common methods can't be ruled out, although the full-collinearity VIFs range from 1.13 to 1.37, which isn't high, so a marker variable or Harman's test is suggested. (iii) The explanatory power of the models is only moderate (R^2 0.14, 0.22), meaning key factors influencing skills and outcomes are not included in the model. (iii) The sample is mostly male (94%) and focused on supervisors and officers in one sector and one country, so the generalizability is limited. (iv) The results are subjectively perceived rather than measured objectively, and interaction tests might be too weak to detect small effects. In future research, long-term designs and/or experimental designs, objective performance measures (like loss, recovery ratios), deployment and/or AI exposure-based multigroup analysis, and other moderators (like leadership support, understanding of AI) can be used.

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