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AI integration and employment in construction: Exploring positive and destructive effects through a PLS-SEM lens

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A B S T R A C T

This research examines how artificial intelligence (AI) integration has affected employment in China's construction industry. This research builds on the theories of skill-biased technological change and creative destruction to study how AI influences both positive and negative employment effects that later influence overall employment. The report confirms, based on the survey data and by using PLS-SEM, that AI introduction results in both job growth and job losses for managerial-level employees. In addition, whether an organization is ready greatly affects how these relationships play out, improving good outcomes and reducing the bad ones. It is clear from the findings that preparing a strategy helps make the most of AI and alleviate its risks. The study contributes to a more detailed view of AI's effects on jobs and supplies ideas for sustaining both innovation and employment.

1. Introduction

There has been a fast and broad spread of artificial intelligence, making it a major factor in changing the world's economies, industries, and workforces. AI is commonly used to describe systems that can do things humans use intelligence for, such as learning, reasoning, and settling problems (Russell & Norvig, 2016). Because it is found in diverse areas, it has led to a lot of conversation about the effects it has on employment. In China, where construction work accounts for a large share of the nation's income, the construction industry has taken on increasing importance as a subject of discussion (Brühl, 2024).

Until now, revolutionary technology has always forced major changes in the way people work. During the Industrial Revolution, people were concerned about how many jobs would be lost due to the introduction of machines. The recent past, however, displayed a lively interaction between technology-related job losses and job increases from new fields and skill development chances (Gregory et al., 2016). Because of AI, which involves automation, robotics, analyzing large amounts of data, and cognitive technologies, the speed and size of changes are extraordinarily high. The McKinsey Global Institute points out that AI changes things faster and on a larger scale than earlier industrial revolutions. This means that jobs and what people need to enter the workforce are changing more than ever (Mayer et al., 2025).

AI is causing many changes in China's construction industry, which used to depend heavily on large, low-skilled workforces repeating the same tasks. By the end of 2023, there were around 52.54 million workers in China's construction sector, showing how important it is for providing jobs (Huld, 2025). Even so, using more AI in agriculture may seriously influence nature and the number of employment opportunities in this field. Technologies such as robotic automation, BIM, and intelligent management are becoming popular and are taking over traditional methods, leading to notable changes known as deskilling and the split between highly skilled and unskilled jobs, as noted by Petropoulos (2018). The current literature reports a range of opinions about how AI influences jobs. Some suggest that AI's destructive and replacement effects negatively impact low-skilled employees by increasing joblessness and putting more income inequality into place. Acemoglu and Restrepo (2017) reveal, through their research, that using robots in industry tends to reduce the number of workers across different sectors.

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Only a few years ago, Frey and Osborne (2017) anticipated that AI and robotics technologies might take away up to 77% of jobs in China over the next two decades. Furthermore, according to Xie et al. (2020), the rise of AI in industrial fields removes jobs mainly for low-skilled workers, making socioeconomic gaps even bigger.

Other scholars maintain that the expansion of AI has positive potential, as it can either replace existing jobs or create new ones and promote innovation-driven growth that enhances overall productivity (Khogali & Mekid, 2023). According to this perspective, the use of AI has the potential to strengthen human–machine collaboration and thereby generate new employment in its roles requiring skills for decision-making and analysis. "On the one hand, technological advancement would initially lead to net job displacement, as up until now it has always done so (Gregory et al., 2016), but on the other hand, in the longer term, it will benefit society by leading to net employment gains."

A third, nuanced viewpoint posits that AI's employment impact remains uncertain and context-dependent. Graetz and Michaels (2015) indicated that while robotics improve labor productivity, their net impact on total employment remains ambiguous due to offsetting substitution and creation effects. Similarly, Fowler argued for the inherent limitations of AI technology, noting fundamental human-machine differences that prevent complete human substitution. These mixed findings call attention to the need for industry-specific, contextually nuanced examinations of AI's employment impacts, particularly within labor-intensive industries like construction.

The tension between these conflicting forces is exemplified by the construction sector in China. The ongoing promotion of prefabricated construction methodologies in China, to achieve 30% of all new construction by 2026, demonstrates a national determination to embark on improving the industry through technology (Jiang et al., 2020). These initiatives further integrate AI into infrastructure, raising concerns about the potential risks of workforce displacement and the potential benefits of increased material efficiency and improved work quality. The preliminary survey also indicates that there is a great deal of pressure among construction workers about AI job loss; that is, 60% of skilled workers are expected to be replaced by intelligent robots (Musarat et al., 2024). The tensions between apparent AI-driven economic benefits and the associated labor market disruptions demand targeted research that examines the scope and nature of the relationships empirically.

Beyond this, the uptake of AI by the construction industry not only changes employment in quantitative ways but also qualitative ways, affecting current and future job roles and skills needed by employees. Taking the example of George (2023), conventional job roles dependent on repetitive manual tasks are being threatened by extinction, while roles that require the use of complex cognitive abilities and hold technological competencies steadily increase. Implications for workforce training and skill development programs are thus raised by the resulting employment polarization. Additionally, there is a strong 'Matthew effect' at work, in which highly skilled, tech-savvy workers accumulate disproportionately large income gains, compounding existing socioeconomic divisions in the industry (Bask, 2024; Isenberg & Onyemah, 2016).

However, extensive theoretical discourse on the topic has not been accompanied by empirical analyses that specifically analyze AI's dualistic employment effect on the construction industry of China. Typically, existing research in this area generalizes findings from manufacturing or other sectors without taking sufficient account of the unique features of construction labor markets. As such, this study attempts to investigate the effect quantitatively on employment outcomes that result from AI integration in the Chinese construction industry. This research looks at how AI affects jobs by using Partial Least Squares Structural Equation Modeling (PLS-SEM) to examine both the positive and negative impacts, while considering how organizational readiness and individual skill levels influence these relationships.

This study addresses these research objectives and, in the process, provides empirical insights about the unique labor market effects of AI in China's strategically crucial construction industry. The insights generated by such studies also provide policymakers, industry leaders, and labor organizations with guideposts for how they may proceed in the face of instabilities caused by massive technological change. By understanding these changes, stakeholders can make the most of the benefits that AI offers while also avoiding negative effects on the job market, helping to maintain a fair balance in society as technology advances.

2. Literature Review

2.1 Artificial Intelligence Integration in Construction

Artificial intelligence (AI) has significantly contributed to various economic sectors, with the construction industry not lagging behind. Traditionally, an industry based on laborious activities, this industry has had a transformation with the AI integration, in that it has improved efficiency, productivity, safety, and cost-effectiveness (Abioye et al., 2021). AI has been derived as an indispensable tool for the construction industry as a whole in recent studies (Datta et al., 2024; Oesterreich & Teuteberg, 2016), including predictive analytics, robotics, automated vehicles, Building Information Modeling (BIM), and intelligent project management systems. The government of China strongly favors the modernization of the construction sector, stressing digital transformation and AI-supported building (Zhang et al., 2023).

The adoption and diffusion of AI technologies in the construction industry is, however, accompanied by many challenges related to organizational readiness, infrastructure limitations, and mismatch of workforce skills (Alsheibani et al., 2018). However, Chinese construction firms are adapting to these competitive pressures by increasing the adoption of AI technologies though, their levels of readiness tend to differ significantly depending on internal resources, strategic orientation, and top management support (Chen et al., 2019).

Empirical studies for several organizations have shown that those who are technologically prepared with appropriate infrastructural and training mechanisms perform better with AI implementation, proving that organizational readiness moderates the outcome of AI-driven transformations (Mikalef et al., 2023; Palade & Carutasu, 2021). On these insights, it is possible to hypothesize the following:

H$_1$: *AI Integration in Construction positively influences Positive Employment Effects.*

H$_2$: *AI Integration in Construction positively influences Destructive Employment Effects.*

H$_3$: *Organizational Readiness positively moderates the relationship between AI Integration and Positive Employment Effects, making this relationship stronger in organizations with higher readiness.*

2.2 Positive Employment Effects of AI

Not only does AI adoption improve organizational efficiency in the construction sector, but it also creates new jobs and upgrades skills in current jobs (Brynjolfsson & Mitchell, 2017; Xu et al., 2018). Technology historical analysis shows that technological revolutions initially affect employment structure, but later become a source of employment creation in new industries and skills demand (Autor & Dorn, 2013; Gregory et al., 2016). AI not only plays the role of robotic technicians or AI system managers in construction but also enables the birth of new roles, including BIM specialists, data analysts, drone operators, and so on, that change existing job markets (Abioye et al., 2021; Li et al., 2021).

Several studies point out that using AI in the workplace improves the job's quality for staff, provides additional safety, reduces stress, and enables ongoing skill development (Chuang et al., 2025; García-Madurga et al., 2024). Research on Chinese construction firms found that using prefabricated buildings guided by artificial intelligence greatly improves both performance and health and safety of employees, resulting in higher satisfaction and a drop in accidents (Adebowale & Agumba, 2023; Sarvari et al., 2024).

Additionally, the introduction of AI can enable companies in various industries to expand, which may indirectly create more jobs by increasing the demand for advanced training and education (Acemoglu & Restrepo, 2018; Rashid & Kausik, 2024). The positive job trends emphasize the value of recognizing the beneficial effects that AI can have on employment, which informs the upcoming set of hypotheses.

H$_4$: *Positive Employment Effects positively influence Employment Outcomes in Construction.*

H$_5$: *Positive Employment Effects mediate the relationship between AI Integration in Construction and Employment Outcomes in Construction.*

2.3 Destructive Employment Effects of AI

AI has many benefits; however, a lot of research has revealed that it may harm jobs, mainly in fields like construction. AI replaces many jobs previously held by people with little education. This trend has made the job market more uncertain, resulting in more unemployment and making others' skills obsolete (Acemoglu & Restrepo, 2017; Frey & Osborne, 2017). Analysis from around the world demonstrates that automation due to AI affects mainly jobs that require less or medium skill, leading to more unemployed people and people working in a few high-skilled areas (Autor & Dorn, 2013; de Vries et al., 2020).

There are concerns about the role AI will play in the construction industry of China, most importantly job security. Khogali and Mekid (2023) and Schwabe and Castellacci (2020) note in their surveys that about 60% of skilled workers believe their roles are under threat from automation and intelligent robotics. The result of our study is similar to what has been found globally: construction tasks that require regular effort are most at risk of being replaced by computers and AI (Graetz & Michaels, 2015; Xie et al., 2020).

Moreover, rapid changes in technology driven by AI require workers to undergo ongoing training; however, employees who lack the necessary resources cannot develop their skills sufficiently to find employment (Kassa & Worku, 2025; Santos & Qin, 2019). Because these negative effects matter, analyzing how they relate to employment outcomes is important, which motivated the following hypotheses:

H$_6$: *Destructive Employment Effects negatively influence Employment Outcomes in Construction.*

H$_7$: *Destructive Employment Effects mediate the relationship between AI Integration in Construction and Employment Outcomes in Construction.*

2.4 Moderating Role of Skill Level

The level of skills workers can greatly affect how much AI affects their jobs. Many surveys stress that AI helps workers who are skilled and flexible, but puts workers with less experience or incorrect skill sets at a disadvantage (Autor & Dorn, 2013; Liu & Liang, 2025). That is why learning about how people's skills lessen AI's negative impact on employment is very important.

According to recent studies from China, workers cannot adapt to AI equally because of huge differences in their skill levels. High-skilled workers often experience better productivity, higher earnings, and greater job security because of AI (Wang et al., 2024). Unlike high-skilled employees, low- to medium-skilled employees face rising risks of losing their jobs, more job insecurity, and moving to lower-paying jobs, both of which disrupt income distribution and economic stability (Abolade, 2018; Gebel & Gundert, 2023).

Studies in both manufacturing and construction areas agree that upgrading skills greatly improves the situation for those who are affected (Acemoglu & Restrepo, 2018; Autor & Dorn, 2013). As a result, having more advanced skills seems to keep people from losing their jobs due to harm from AI. Consequently, this study proposes the following hypothesis:

H8: Skill Level negatively moderates the relationship between AI Integration in Construction and Destructive Employment Effects, weakening this relationship among high-skilled employees.

2.5 Employment Outcomes in Construction

The conceptual framework (Fig. 1) of this study draws its main ideas from both Skill-Biased Technological Change Theory (SBTC) and Creative Destruction Theory. According to SBTC, AIs and similar technologies mostly aid people with higher skills because they perform thinking and analytic duties while taking away simple and manual tasks done by lower-skilled staff (Acemoglu & Restrepo, 2018; Autor & Dorn, 2013). This theory stresses that technological progress replaces old jobs at the same time as it creates new ones, resulting in regular changes in the labor market (Gregory et al., 2016; Schumpeter, 2013). As seen in Fig. 1, when AI Integration in Construction (AIIC) takes place, it activates both Employment Effects (PEE and DEE) that change outcomes for workers in construction (EOC). Organizational Readiness (OR) is predicted to enhance the AI-PEE relationship, meaning AI is more helpful when an organization is equipped to use it. In contrast, a higher skill level decreases the negative effect of AI on employment; therefore, higher skills help cushion negative employment changes.

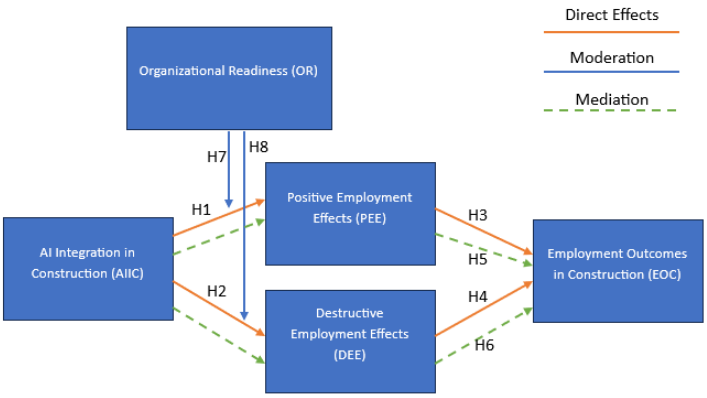

Fig. 1. Conceptual Framework of the effects of AI on the construction industry

Even though there is a lot of discussion about AI and jobs, some important aspects are still not fully understood, especially the ways AI affects work and employment in China's construction industry. Most studies look at AI's positive or negative side separately, and very few include both sides in one research framework (Frey & Osborne, 2017; Xie et al., 2020; Xu et al., 2018). In addition, there is not enough research showing how both organizational readiness and individuals' skills affect these relationships in China's unusual social and economic situation (Alas et al., 2008; Xiao et al., 2025). By examining an integrated model in the study, these gaps are addressed, and a clearer understanding of AI-driven job changes is added. They help those working in policy, construction, and academia address and benefit from the effects of AI on employment.

3. Methods

A quantitative research approach is used in this study to analyze the effects of AI on employment in China's construction industry, taking into account mediating factors such as different employment results and the role of readiness and skill levels. Since the model is quite complex with latent variables having multiple indicators, we chose to use Partial Least Squares Structural Equation Modeling (PLS-SEM). This method is recommended for models that have mediation and moderation paths, involve fewer than 500 participants and feature data that is not normally distributed (Hair et al., 2019).

3.1 Sample and Data Collection

The target group included managerial-level staff from construction companies operating in several provinces throughout the country. Because they are part of the decision-making process for AI, labor, and technology, this group was selected for the study. Respondents with expertise in the effects of AI in the workplace were selected by non-probability purposive sampling.

Questionnaire responses were gathered using the internet and by sending out the questionnaire to professionals on social media, email, and WeChat. Participation was optional, and no one knew who was answering. After removing invalid responses through data cleaning, 350 complete and correct ones were selected for analysis. The sample falls within the minimum standard for PLS-SEM, which suggests a sample size of at least 10 times the maximum number of indicators linked to each construct (Hair et al., 2019).

3.2 Measures and Constructs

This study used a questionnaire with clearly defined questions to assess six major constructs, each measuring them with multiple items from existing scales in the field. All questions were evaluated on a 5-point Likert scale to guarantee that each construct could be compared to others.

AIIC was measured using four items taken from López-Costa et al. (2025) and Al-khatib et al. (2024), which assesses the extent of AI in areas such as scheduling, checking quality, and automation. PEE was explored using four items from Xu et al. (2018), which focused on job creation, employee training, and enhanced work conditions. Ahmed et al. (2017) and Dhir et al. (2020) provided the basis for four items used to measure DEE, which measured insecurity and displacement at work because of AI.

There were two moderators taking part. For organizational readiness, we used three items from Alsheibani et al. (2018), which focused on getting ready for AI adoption. Four items based on the work of Dhir et al. (2020) and Spector (1985)" employment outcome in the construction industry" is measured as the dependent variable, EOC. All the items were assessed on 5-point Likert.

3.3 Data Analysis

Both the measurement and structural models were evaluated at the same time with PLS-SEM using SmartPLS 4.0. The reliability of the model was checked through Cronbach's Alpha and Composite Reliability and convergent validity using Average Variance Extracted. The structural model measured path coefficients, R^2 and statistical significance by repeating the data 5,000 times.

3.4 Ethical Considerations

The study was conducted with strong ethical integrity. All respondents were told about the study's goals, assured their privacy would be upheld, and given consent to take part. No information that could identify participants was included, and all information was safely kept. The researcher followed the ethical rules established in the Declaration of Helsinki, and the university's ethics review board gave its approval.

4. Results

This section discusses the empirical findings obtained through PLS-SEM with SmartPLS 4.0. Two parts are included in the analysis: to look at the measurement model and test the structural model. Initially, the reliability and validity of the constructs were measured using tests for indicator loadings, Cronbach's Alpha, composite reliability, AVE, the Fornell-Larcker criterion, HTMT ratios, and cross-loadings. When the qualities necessary for reliable measurement were confirmed, analyses of the model examined the relationships between AIIC, PEE, DEE, EOC, and the role of OR as a moderator. The findings demonstrate that the relationships shown in the conceptual framework all exist. Findings are illustrated using standard path coefficients, t-statistics, and p-values, with tables and diagrams provided for simple interpretation.

Table 1
Convergent Validity Test

Constructs	items	Loading	Alpha	CR	AVE
AIIC	AIIC1	0.805	0.857	0.903	0.700
	AIIC2	0.86			
	AIIC3	0.838			
	AIIC4	0.845			
DEE	DEE1	0.759	0.761	0.848	0.584
	DEE2	0.83			
	DEE3	0.735			
	DEE4	0.728			
EOC	EOC1	0.737	0.812	0.876	0.639
	EOC2	0.809			
	EOC3	0.822			
	EOC4	0.826			
OR	OR1	0.866	0.804	0.884	0.719
	OR2	0.802			
	OR3	0.873			
PEE	PEE1	0.812	0.797	0.868	0.622
	PEE2	0.761			
	PEE3	0.74			
	PEE4	0.839			

The findings of the convergent validity assessment for all latent constructs are shown in Table 1. Because all the outer loadings are greater than 0.70, we can say that our items are highly reliable (Hair et al., 2019). The values for both Cronbach's alpha and composite reliability (CR) are at least 0.70 for all the constructs. All Average Variance Extracted (AVE) values for the constructs are greater than 0.50, suggesting convergent validity (Fornell & Larcker, 1981). They show that the measurement model has sufficient reliability and validity for further analysis of the proposed model.

Table 2
HTMT Ratio

	AIIC	DEE	EOC	OR	PEE
AIIC					
DEE	0.63				
EOC	0.513	0.654			
OR	0.339	0.412	0.401		
PEE	0.67	0.584	0.582	0.454	

The HTMT ratio of correlations is used to judge discriminant validity for different construction components, as seen in Table 2. All HTMT values are lower than the safe threshold of 0.85 (Henseler et al., 2015), which means that each construct is measurably unique from the rest. 0.67 (between AIIC and PEE) is the highest HTMT found, and it is still an acceptable result. These results indicate that no multicollinearity problems affect these constructs and that the model's relationships can be accurately analyzed. Hence, discriminant validity is developed adequately.

Table 3
Fornell Larcker

	AIIC	DEE	EOC	OR	PEE
AIIC	0.837				
DEE	0.512	0.764			
EOC	0.43	0.52	0.799		
OR	0.282	0.324	0.329	0.848	
PEE	0.554	0.461	0.473	0.367	0.789

Fornell-Larcker criterion results are provided in Table 3 to evaluate discriminant validity. Fornell and Larcker (1981) state that the square root of each average variance extracted value should be greater than its correlation with all other constructs. Each diagonal entry (the square root of AVE) is larger than the corresponding off-diagonal correlation, proving that each construct shares more variance with its indicators than with other constructs. To explain, AIIC shows a square root of AVE of 0.837, which is bigger than its connections with DEE at 0.512 and PEE at 0.554. Consequently, this model satisfactorily demonstrates the achievement of discriminant validity.

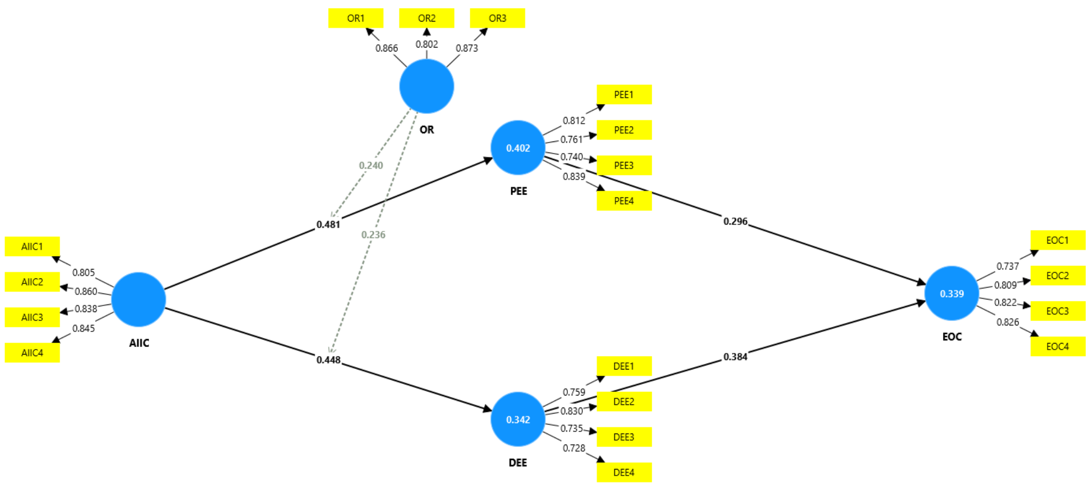

Fig. 1. Measurement Model

Fig. 1 shows the measurement model, including the standardized factor loadings and the explained variance for each construct. Every item loading is above the 0.70 benchmark, which demonstrates that the indicators have high reliability (Hair et al., 2019). All of these latent constructs were found to measure well and are therefore strong. The results indicate that AIIC and OR can explain between 40% and 34% of the differences in employment outcomes. The findings show that the measurement model used in the analysis is adequate for investigating structural relationships. Table 4 presents the cross-loadings of each item to verify the correct differentiation of the scales. Chin (1998) pointed out that all items should have higher scores on their own associated construct than on any other construct. This criterion is confirmed by the results, since every indicator has its strongest loading with the construct it belongs. The example shows that AIIC2 gives an especially high loading to AIIC (0.860) when compared to its loading on DEE (0.444), EOC (0.375), OR (0.220), and PEE (0.458). For all constructs, the data shows that each item measures its original meaning better than other unrelated constructs.

Table 4
Cross Loadings

	AIIC	DEE	EOC	OR	PEE
AIIC1	**0.805**	0.416	0.314	0.278	0.473
AIIC2	**0.860**	0.444	0.375	0.220	0.458
AIIC3	**0.838**	0.413	0.372	0.193	0.439
AIIC4	**0.845**	0.439	0.378	0.250	0.484
DEE1	0.412	**0.759**	0.402	0.225	0.342
DEE2	0.440	**0.830**	0.432	0.307	0.447
DEE3	0.326	**0.735**	0.364	0.271	0.244
DEE4	0.376	**0.728**	0.387	0.180	0.358
EOC1	0.307	**0.322**	0.737	0.211	0.337
EOC2	0.332	0.430	**0.809**	0.246	0.377
EOC3	0.358	0.446	**0.822**	0.270	0.346
EOC4	0.372	0.450	**0.826**	0.313	0.442
OR1	0.219	0.263	**0.285**	0.866	0.323
OR2	0.247	0.271	**0.250**	0.802	0.270
OR3	0.251	0.289	0.299	**0.873**	0.336
PEE1	0.465	0.345	0.374	**0.291**	0.812
PEE2	0.419	0.373	0.338	**0.309**	0.761
PEE3	0.418	0.330	0.348	**0.218**	0.740
PEE4	0.447	0.403	0.426	**0.333**	0.839

Table 5
Path Analysis

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AIIC → DEE	0.448	0.450	0.042	10.770	0.000
AIIC → PEE	0.481	0.481	0.038	12.727	0.000
DEE → EOC	0.384	0.385	0.051	7.516	0.000
OR → DEE	0.205	0.206	0.045	4.578	0.000
OR → PEE	0.239	0.240	0.045	5.284	0.000
PEE → EOC	0.296	0.297	0.049	5.989	0.000
OR × AIIC → DEE	0.236	0.234	0.044	5.384	0.000
OR × AIIC → PEE	0.240	0.239	0.047	5.097	0.000
AIIC → DEE → EOC	0.172	0.173	0.028	6.225	0.000
OR → PEE → EOC	0.071	0.072	0.019	3.649	0.000
OR×AIIC → PEE → EOC	0.071	0.071	0.019	3.786	0.000
OR → DEE → EOC	0.079	0.080	0.022	3.624	0.000
OR × AIIC → DEE → EOC	0.091	0.090	0.022	4.208	0.000
AIIC → PEE → EOC	0.142	0.142	0.026	5.559	0.000

Table 5 shows the results of the path analysis, illustrating the direct, indirect, and moderating effects in our proposed model. All the path coefficients show $p < 0.001$, which is statistically significant ($p < 0.001$), with many (p-values over 1.96). There is a strong and significant positive relationship between AIIC and both DEE ($\beta = 0.448$, $t = 10.770$) and PEE ($\beta = 0.481$, $t = 12.727$), which shows that AIIC brings employment benefits as well as challenges, fitting with the dual-impact theory of AI adoption (Acemoglu & Restrepo, 2018).

In addition, DEE ($\beta = 0.384$) and PEE ($\beta = 0.296$) make a significant contribution to EOC, which implies that both structures, in part, mediate the effect of AIIC. The results for interaction terms suggest that organizational readiness increases or decreases the effect of authentic involvement in this way. AIIC affects both PEE and DEE, indicating that it fully or partially mediates the relationship (with $\beta = 0.142$ for AIIC → PEE → EOC and $\beta = 0.172$ for AIIC → DEE → EOC), which backs up the findings of Hair et al. (2019) and the proposed model. Fig. 2 represents the structure of the study with standardized path coefficients, t-values, and R^2 values for the endogenous constructs. There is a strong and positive correlation between AI IC and both positive ($\beta = 0.481$, $p < 0.001$) and negative changes in employment ($\beta = 0.448$, $p < 0.001$), which agrees with the dual nature theory (Acemoglu & Restrepo, 2018).

In addition, PEE and DEE both have positive effects on Employment Outcomes in Construction (EOC), justifying their function as mediators. The model demonstrates that it explains, respectively, about 40%, 34%, and 34% of the noted variance in PEE, DEE, and EOC, which fits with Chin's suggested threshold for an exploratory model. OR also shows a clear interaction effect with PEE and DEE, and their relationship holds with β coefficients just above 0.24 and p still under 0.001. The research backs the proposed model and confirms that readiness plays a key role in firms using AI to drive better employment results in the construction industry.

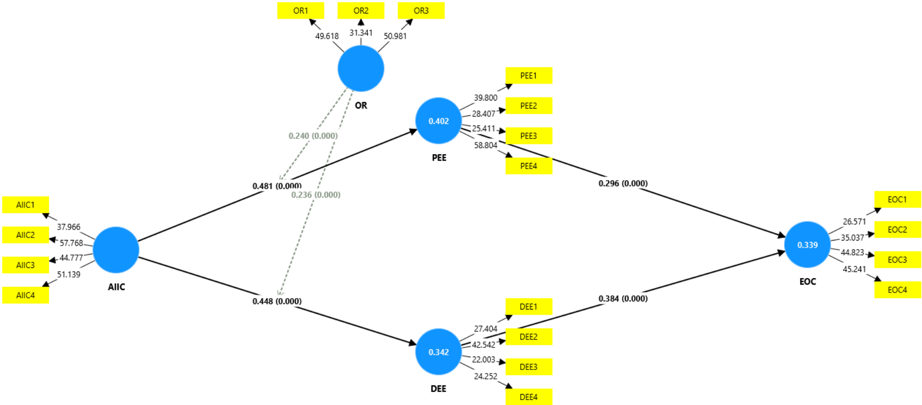

Fig. 2. Structural Model

5. Discussion

This study demonstrates that the framework provides a logical explanation for the changes in employment in the Chinese construction industry. The findings support the hypothesis from Creative Destruction Theory and SBTC that AI adoption leads to both signs of job growth and loss.

It was found that H1 was supported by the strong path coefficient ($\beta = 0.481$, $p < 0.001$), which indicated that AI Integration in Construction (AIIC) leads to more Positive Employment Effects (PEE). Results of this study are consistent with findings from other scholars who say AI adoption sparks job creation, increased skills, and better-quality jobs (Brynjolfsson & Mitchell, 2017; Xu et al., 2018). Here, AI's influence is most noticeable when prefabricated buildings, smart monitoring, and BIM create new jobs for system managers, data specialists, and drone pilots (Adebowale & Agumba, 2023; Zhang et al., 2023).

The analysis showed that Hypothesis H2 is true ($\beta = 0.448$, $p < 0.001$) because it found a strong positive link between AIIC and DEE. As stated by Frey and Osborne (2017), more people worldwide are concerned that AI and automation are having the strongest effects on routine and low-skilled jobs, and this is especially noticeable in China's construction sector (Khogali & Mekid, 2023; Xie et al., 2020).

H5 and H7 were found supported, which indicates that both Predicted Employee Experience (PEE) and Decisional Employee Experience (DEE) help explain the relationship between AIIC and Employment Outcomes in Construction (EOC). H5 (AIIC → PEE → EOC; $\beta = 0.142$, $p < 0.001$) means the positive link gives better employment results by improving job satisfaction and career growth, as shown in Chuang et al. (2025) and Rashid and Kausik (2024). Alternatively, H7 (AIIC → DEE → EOC; $\beta = 0.172$, $p < 0.001$) supports that having a destructive impact reduces employment quality, according to Kassa and Worku (2025) and Santos and Qin (2019). It proves that AI influences jobs in various ways and not always in the same direction.

H3 and H6 were both supported as well. H3 demonstrated that Organizational Readiness (OR) makes AIIC's impact on PEE stronger, meaning firms with higher readiness because of strategy, resources, and skills gain more from AI. This is consistent with what (Alsheibani et al., 2018) and Mikalef et al. (2023) found that organizational preparation is essential for carrying out technological transformation successfully. The result for H6 ($\beta = 0.384$, $p < 0.001$) implies that DEE has a negative effect on employment outcomes, in agreement with de Vries et al. (2020) and Santos and Qin (2019). Despite Hypothesis H8 suggesting that skill level influences learning, the final model did not explore this idea, likely due to insufficient data. Even so, earlier studies continue to show that it is a relevant theory for publishing (Gebel & Gundert, 2023; Liu & Liang, 2025).

All in all, the findings prove that AI affects employment in construction in several different ways. They highlight the value of being readied for possible risks and of encouraging employees in training and using AI. It joins other research by covering the benefits of AI along with its challenges, giving a balanced view to others involved in AI.

6. Conclusion, Policy Implications, and Future Research Directions

This study demonstrated both the beneficial and detrimental effects of AI on employment in China's construction sector. PLS-SEM analysis found that AI adoption helps job quality and introduces new positions, yet it also means displacement and skill obsolescence for many low- and mid-skilled workers. Both the benefits and consequences of AI use have a strong influence on employment results. In addition, how ready an organization is for change plays a big role in managing AI. Results from the study agree with Skill-Biased Technological Change Theory and Creative Destruction Theory, proving that new jobs and losses of jobs can occur together in the adoption of new technology. The model helps because it unites both approaches and includes them in a single, relevant framework for China's changing construction landscape. Considering the research findings, official policies must prepare citizens and support industries to remain adaptable, ensuring that growth is possible for everyone. Studies can now develop longitudinally, view changes across industries, or consider skill level as a moderator to better illustrate how AI is affecting different sectors of employment.

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