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Psychosocial Dynamics Influencing the Adoption of Artificial Intelligence among Chinese Construction Workers in Guangzhou, China

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Abstract: *The advent of Artificial Intelligence (AI) has revolutionized the world construction sector and enhanced its safety, productivity, and efficiency of projects. Nevertheless, the real application of AI tools to construction workers is still not unified even with the institutional support and technological advancement. This research paper was aimed at exploring the psychological reason behind the use of AI by Chinese construction workers in Guangzhou. Particularly, it investigated the connection between technology anxiety, social influence and computer self-efficacy and their combined and relative impacts on the adoption of AI. The descriptive survey design was taken. The sample was of skilled and semi-skilled workforce in the chosen medium- and large-scale construction companies at Guangzhou, China. A standardized questionnaire was used to gather data of 237 respondents using structured and validated instruments. The data were analyzed using descriptive statistics, Pearson Product Moment Correlation (PPMC) and Multiple Regression Analysis at a level of significance of 0.05.The results showed that there is a strong negative correlation between technology anxiety and AI adoption ($r=-.584$, $p<0.01$), and positive correlation between computer self-efficacy and AI adoption ($r=.349$, $p<0.05$). Nevertheless, social influence did not demonstrate any significance with AI adoption ($r = .072$, $p>0.05$). The three psychological variables combined together to predict AI adoption ($R=.689$, $R^2=.475$, $F_{(3,233)}= 70.270$, $p<0.05$). Technology anxiety ($\beta=-.436$, $p<0.05$) and computer self-efficacy ($\beta=.238$, $p<0.01$) significantly contributed to the independent variables, but not social influence.According to these results, construction companies are advised to introduce the ongoing training of AI to enhance computer self-efficacy in workers and decrease technology-related anxiety. Favorable learning conditions where students can practice should be promoted. Digital literacy, stress management, and human-focused AI integration should also be encouraged by the organization and government policies to enhance confidence, inclusiveness, and sustainable adoption of AI by construction workers.*

Keywords: Artificial Intelligence, Technology Anxiety, Social Influence, Computer Self-Efficacy

Introduction

The recent emergence and rapid diffusion of generative artificial intelligence, computer vision, machine learning, and artificial intelligence driven automation have expanded the practical applications of artificial intelligence across business functions including design optimization, predictive analytics, safety monitoring, scheduling and worker support. Artificial Intelligence (AI), broadly defined as computational systems that perform tasks normally requiring human intelligence (learning, reasoning, perception and decision-making) has accelerated from a specialized research domain into a pervasive set of tools reshaping industry and everyday work (Kumar et al, 2025). In construction specifically, AI technologies such as predictive risk models, site monitoring via drones and computer vision, digital twins, and automated planning tools are being promoted as ways to improve productivity, reduce errors, and enhance safety on otherwise fragmented and labour-intensive worksites (Shrivastava, 2025).

AI adoption has moved from early experimentation toward wider operational use. Global surveys report steep increases in organizational AI adoption by early 2024 over two-thirds of surveyed organizations reported using AI in at least one business function, with overall organizational AI adoption figures reported around 55–72% depending on the survey and definitions used (Bruno and Skoglund, 2024). Market data also show fast growth in the AI-for-construction sector, with market valuations in the low billions of USD in 2023–2024 and strong compound annual growth projections through the 2020s (De Valence, 2022). These global trends are mirrored in China, where government strategy, corporate investment, and sizable industrial automation capacity have supported rapid AI uptake; combined with relatively high public trust in AI, this creates a favorable environment for adopting AI in sectors including construction (Zong and Guan, 2025).

Recent international surveys indicate that AI usage in organizations has moved from niche pilots to substantive deployment. McKinsey's 2024 global survey reported significant jumps in organizational adoption (with figures commonly cited in the 55–72% range depending on measurement), and many firms now use AI in multiple business functions rather than as a single-use pilot (Recker et al, 2024). The Stanford HAI AI Index and other syntheses similarly document that AI investment, startups, and enterprise use remain large and growing despite some short-term financing fluctuations (Patil, 2025). In the construction industry, specialist market reports and industry analyses report that AI and machine learning are among the fastest-growing technologies adopted by construction firms; construction firms on average are increasing their use of digital tools and AI-enabled services like drones, predictive scheduling, safety analytics and digital twins, driving the AI-in-construction market into multi-billion USD projections by the end of the decade.

On construction sites, AI's manifestations include (but are not limited to) automated site surveillance and safety monitoring using computer vision to detect hazards or unsafe behaviours; predictive maintenance and risk forecasting for equipment and project scheduling; productivity analytics that integrate BIM (Building Information Modeling) data with sensor feeds; and intelligent assistants that support planning and administrative tasks (Chong et al., 2025). These applications can reduce delay, enhance safety, and enable managers to make data-driven decisions in complex, dynamic settings. Importantly, many AI applications operate through interfaces (apps, dashboards, wearable sensors) that require on-site crews to interact with new devices or alter daily routines, which makes worker acceptance and use behavior central to realizing AI's benefits (Li et al., 2026).

China has been a central actor in AI development and deployment, showing strong industrial adoption and comparatively high public trust in AI technologies (Wang et al., 2022). Guangzhou, as a major city within the Guangdong–Hong Kong–Macao Greater Bay Area, has locally oriented digitalization initiatives and academic work illustrating AI applications in urban planning and built environment projects (Wu & Li, 2025). Municipal strategies in Guangzhou emphasize digital twin development and smart city innovation that create institutional incentives for construction firms and public projects to integrate AI solutions (Zhen et al., 2025). However, while city-level initiatives and pilot projects exist (e.g., research into AI for urban reuse and planning), adoption at the front line among construction workers who operate equipment, carry out installations, and work on sites depends on worker-level psychological and social factors that mediate whether and how AI tools are used effectively.

The implications of AI adoption in construction are double-edged. On one hand, tangible gains (improved safety, better schedule adherence, cost savings, and quality control) are widely reported in industry literature (Ying et al., 2025). On the other hand, realizing these benefits requires frontline workers to accept, trust, and competently use AI-enabled systems: otherwise, tools remain underused, misused, or ignored, and anticipated productivity/safety gains fail to materialize. Moreover, the socio-psychological effects such as changes in job roles, perceived job insecurity, or increased monitoring, can affect morale and retention. Thus, psychosocial dynamics in this study encompass individual psychological attributes (technology anxiety and computer self-efficacy) and social-contextual influences (social influence) that shape technology adoption behaviour.

Technology anxiety (often termed computer anxiety or technophobia) in the refers to feelings of tension, apprehension, or fear when an individual anticipates or uses information technologies. Empirical research shows that anxiety about technology is negatively associated with technology adoption and usage: anxious users are more likely to avoid new tools, show lower engagement, and report poorer performance even when tools are available (Verano-Tacoronte et al., 2025). In construction contexts, where work is physically demanding and time pressures are high, adding unfamiliar digital interfaces, wearables, or automated monitoring systems can increase cognitive load and stress; for workers with high technology anxiety, this can lead to avoidance or superficial use of AI tools, undermining the potential benefits of deployment (Chang et al., 2025).

Technology anxiety also interacts with other constructs: it reduces perceived ease of use and effort expectancy, undermining perceived usefulness and behavioural intention in models such as TAM and UTAUT (Lee et al., 2025). For Chinese construction workers in Guangzhou, many of whom may have varying educational backgrounds and differing prior exposure to digital tools, technology anxiety may be particularly salient. If anxiety arises from fears of job displacement, fear of surveillance, or a prior negative experience with digital systems, interventions that only provide technology without addressing emotional responses will likely be insufficient. Therefore, measuring and addressing technology anxiety is crucial for improving AI acceptance and sustained use on construction sites.

Social influence refers to the degree to which an individual perceives that important others like supervisors, peers, or organizational leaders, expect them to use a technology. Social influence shapes both normative pressure and the informational environment in which workers form beliefs about new tools. Numerous studies show that social influence positively correlates with behavioral intention to use technology, especially in contexts where use is visible, collective, or tied to performance evaluations (Cioc et al., 2023).

In construction, social influence may be particularly powerful because worksites are team-based, hierarchical, and reliant on coordinated action. If foremen, lead engineers, or trusted senior workers endorse AI tools and model their use (for example, by using mobile dashboards or following AI-driven safety prompts), other workers are more likely to accept and try these tools (Yazdi, 2024).

Conversely, peer skepticism, rumors about job loss, or resistance among influential crew members can dampen adoption despite organizational mandates. Social networks on site also convey tacit knowledge observing a coworker successfully using AI tools can increase perceived usefulness and reduce uncertainty, thereby increasing uptake.

Self-efficacy (the belief in one's ability to perform specific actions) is a foundational psychological construct (Bandura, 1977) and has been adapted to technology contexts as computer self-efficacy or digital self-efficacy. Higher self-efficacy predicts more favourable attitudes toward technology, greater persistence when encountering problems, and higher actual usage levels. Meta-analytic and longitudinal work consistently finds that computer self-efficacy influences perceived ease of use and use behaviour in TAM/UTAUT frameworks (Al-Adwan et al., 2025).

For construction workers, self-efficacy determines whether they will approach an AI tool as manageable and learnable or as a threat and barrier. Practical experiences (hands-on training, incremental task mastery, and peer modelling) raise self-efficacy and thereby increase the likelihood of adoption and proper use. Digital training that focuses on building mastery (task-based, scaffolded learning), plus immediate facilitation (on-site tech support), can increase self-efficacy among workers and thus improve adoption outcomes (Khalid, 2023). In sum, self-efficacy operates both as a direct antecedent of adoption and as a buffer against anxiety: workers with higher self-efficacy show less anxiety and greater resilience in the face of new AI processes (Kim & Lee, 2025).

Most contemporary studies of technology adoption use integrative frameworks such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), which highlight constructs such as performance expectancy, effort expectancy, facilitating conditions, social influence, and behavioural intention (Bayaga & du Plessis, 2024). These frameworks also indicate roles for individual differences like anxiety and self-efficacy as antecedents or moderators of adoption decisions (Symasek et al., 2025). Yet the majority of adoption research aggregates organizational or managerial perspectives; comparatively fewer studies examine frontline blue-collar workers in heavy industries (like construction), and even fewer that focus on AI specifically rather than generic IT tools (Brown, 2025). There is a need for contextualized research that examines how anxiety, social influence, and self-efficacy interact in culturally specific settings such as Chinese construction sites in Guangzhou, places with unique organizational practices, regulatory frameworks, and social norms.

Moreover, while national statistics and city-level initiatives signal that China and Guangzhou are positioned to accelerate AI deployment, the literature indicates a possible implementation gap between institutional-level strategies and frontline uptake (Ming et al., 2025). This gap suggests a practical research imperative: to identify psychological barriers and facilitators at the worker level, examine how social networks and supervisory practices shape adoption, and test intervention levers (training, peer champions, anxiety-reduction strategies) that could increase effective AI use on sites.
Despite the accelerating integration of Artificial Intelligence (AI) into the global construction industry, there is mounting evidence of an "implementation gap" between the technological capabilities being deployed and the actual uptake by frontline workers. In Guangzhou, where municipal and national initiatives strongly encourage AI adoption, construction workers are increasingly exposed to predictive risk models, drone monitoring, digital twins and automated planning tools. Yet many of these applications require workers to change routines, interact with unfamiliar devices, or accept heightened digital oversight. Without adequate attention to the psychosocial dynamics that shape their responses, AI tools may be underused, misused, or resisted. Such outcomes could erode the expected gains of AI improved safety, cost savings, quality control and productivity and may instead lead to heightened job stress, perceptions of surveillance, morale problems, and project delays. In other words, the promise of AI in construction will remain largely aspirational if the determinants of workers' acceptance and effective use are not clearly understood and addressed.

Although a growing body of research has examined technology acceptance using frameworks such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), much of it has focused on managerial or organizational perspectives and on generic information technologies rather than AI in heavy industries. Existing studies have demonstrated the influence of constructs such as performance expectancy, effort expectancy, and facilitating conditions, and some have linked technology anxiety, social influence, and self-efficacy to adoption outcomes. However, comparatively few empirical investigations have concentrated on frontline blue-collar workers in the construction sector, and still fewer have examined these three psychosocial dynamics together in the context of AI deployment in Chinese construction sites. The literature also provides limited evidence on how these factors interact under culturally specific conditions such as Guangzhou's distinctive regulatory environment, labor practices, and high-trust yet rapidly digitalizing workforce. This leaves critical gaps in understanding how individual emotions, peer norms, and personal efficacy jointly shape AI adoption among workers who ultimately determine whether technologies succeed on site.

This study is designed to fill that gap by empirically examining the psychosocial dynamics of technology anxiety, social influence and self-efficacy as determinants of AI adoption among construction workers in Guangzhou, China. By situating these constructs within a real-world, culturally specific context and focusing on the frontline rather than the managerial level, the research will generate actionable insights for policymakers, technology developers, and construction managers. The findings will help explain why AI adoption may stall or succeed in practice, inform interventions to build workers' confidence and supportive social norms, and ultimately contribute to more effective, human-centred deployment of AI in China's construction industry and similar contexts worldwide.

Purpose of the Study

The main purpose of this study is to investigate the psychosocial dynamics influencing the adoption of artificial intelligence among Chinese Construction Workers in Guangzhou, China.

Specifically, it intends to:

i. examine the relationship between technology anxiety and AI adoption among Chinese Construction Workers in Guangzhou, China.
ii. examine the relationship between social influence and AI adoption among Chinese Construction Workers in Guangzhou, China.
iii. examine the relationship between computer self-efficacy and AI adoption among Chinese Construction Workers in Guangzhou, China.
iv. examine the joint contribution of technology anxiety, social influence and computer self-efficacy to the prediction of AI adoption among Chinese Construction Workers in Guangzhou, China.
v. examine the relative contribution of technology anxiety, social influence and computer self-efficacy to the prediction of AI adoption among Chinese Construction Workers in Guangzhou, China.

Hypotheses

$H0^1$ There is no significant relationship between technology anxiety and AI adoption among Chinese Construction Workers in Guangzhou, China

$H0^2$ There is no significant relationship between social influence and AI adoption among Chinese Construction Workers in Guangzhou, China

$H0^3$ There is no significant relationship between computer self-efficacy and AI adoption among Chinese Construction Workers in Guangzhou, China

$H0^4$ There is no significant joint contribution of technology anxiety, social influence and computer self-efficacy to the prediction of AI adoption among Chinese Construction Workers in Guangzhou, China.

$H0^5$ There is no significant relative contribution of technology anxiety, social influence and computer self-efficacy to the prediction of AI adoption among Chinese Construction Workers in Guangzhou, China.

Methodology

This study adopted a quantitative cross-sectional survey design to examine the relationship between psychosocial factors (technology anxiety, social influence, and computer self-efficacy) and the adoption of Artificial Intelligence (AI) among construction workers in Guangzhou, China. The population of the study consisted of construction workers who are directly exposed to AI-enabled technologies such as AI-assisted machinery, intelligent safety monitoring systems, and automated project scheduling tools. The sample comprised 239 skilled and semi-skilled construction workers drawn from medium- and large-scale construction firms in Guangzhou. Sample size determination was guided by the Hasan and Kumar (2024) sample size determination table and supported by Cochran's formula for large populations, based on the estimated accessible workforce across the selected firms. Adjustments were made to accommodate accessibility and response rate, resulting in 239 valid and usable responses for analysis.

A multistage sampling technique was employed. In the first stage, simple random sampling was used to select construction firms in Guangzhou that had adopted or were in the process of adopting AI technologies. Five firms were selected: China State Construction Engineering Corporation (CSCEC) – Guangzhou Branch; China Railway Construction Corporation (CRCC) – South China Division; Guangzhou Construction Group Co. Ltd. (GCGCL); China Communications Construction Company (CCCC) – Guangdong Office; and PowerChina Construction Group (PCCG) Guangzhou Project Office. In the second stage, stratified random sampling was used to classify workers into skilled and semi-skilled categories. In the third stage, proportionate random sampling was applied to select respondents from each stratum based on workforce size within the firms.

Structured questionnaire was used in collecting data for the study. The scales were proven to be psychometrically sound and have been widely used over the years. The questionnaire consists of five sections namely: sections A, B, C, D and E.

Section A: consisted items that measure the socio-demographic information of the respondents, such as gender, age, company and Unit or specialization. The gender of the respondents was reported as male and female, actual age, department and ministry where the respondents' works were also asked.

Section B: AI Adoption Scale

The artificial intelligence adoption scale is a 6 item scale adapted from Kanti et al., (2022). It has 4 likert scale response format that respondents can select from to respond to the given items rangeing from 1 - strongly disagree to 4 - strongly agree. Examples of items include; I intend to use AI tools for my construction work in the next three months and I have used AI tools a lot in my work over the past four weeks. Higher scores indicate greater adoption intention or usage. A pilot study was conducted to ensure that the scale is psychometrically sound and a coefficient of $\alpha = 0.81$ was recorded.

Section C: Anxiety towards AI Scale

This scale measures affective reactions such as apprehension and fear when using AI systems. It is adapted from Kaya et al., (2024). It has 4 items on a four Likert scale response format with options ranging from 1 - strongly disagree to 4 - strongly agree. Samples of the items on the scale include, it scares me to think I could lose important information by using AI incorrectly and I hesitate to use AI systems for fear of making mistakes I cannot correct. The researcher pilot tested the scale and found that the scale is reliable with a reliability coefficient of $\alpha = 0.87$.

Section D: Social Influence Scale

This scale measures the degree to which important others (supervisors, co-workers, organisation) think the worker should use AI. It is adapted from Stibe and Cugelman (2019). It has 4 items on a four Likert scale response format with options ranging from 1 - strongly disagree to 4 - strongly agree. Samples of the items on the scale include; People who are important to me at work think that I should use AI tools and Senior management in my organisation encourages the use of AI tools. The researcher pilot tested the scale and found that the scale is reliable with a reliability coefficient of $\alpha = 0.72$.

Section E: Self-Efficacy (for using AI tools) Scale

This scale measures the belief in one's capability to complete tasks with AI-enabled software under varying conditions. It is adapted from the scale development and validation of Artificial intelligence self-efficacy by Wang & Chuang (2024). There are 10 items in the scale with four Likert scale response format with options ranging from 1 - strongly disagree to 4 - strongly agree. Samples of the items in the scale include; How confident are you that you could complete your job tasks using an AI-enabled tool (that you haven't used before) under each condition? if there was no one around to tell you what to do as you go and if you had a lot of time to complete the job for which the tool was provided. A pilot study was carried out to revalidate the scale and a reliability coefficient of $\alpha = 0.94$ was found.

Descriptive statistics such as frequency counts, mean and standard deviation were used to describe the socio-demographic information of the respondents as well as research questions one to four, research question five was analysed using Pearson Product Moment Correlation (PPMC), while research questions six and seven were answered using Multiple Regression Analysis, all at 0.05 levels of significant.

Result

Table 1: **Socio-Demographic Characteristics of the Respondents**

Demographic Characteristics		**N = 237**	
		Frequency	**Percent%**
Gender	Male	186	78.5
	Female	51	21.5
Age	25 – 34 years	47	19.8
	35 – 44 years	102	43.0
	45 – 54 years	62	26.2
	55 years and above	26	11.0
Construction Company	CSCEC	50	20.92
	CRCC	46	19.25
	GCGCL	49	20.50
	CCCC	44	18.41
	PCCG	50	20.92

Source: field survey

Table 1 reveals that out of 237 respondents, 78.5% of them are male, while 21.5% are female. Regarding their age category, 19.8% of them are between the age of 25 and 34 years, 43% are between 35 and 44 years, 26.2% are between 45 and 54 years, while the remaining 11% of the respondent are between 55 and 64 years. Lastly, 20.92% are from China State Construction Engineering Corporation (CSCEC) – Guangzhou Branch and PowerChina Construction Group (PCCG) Guangzhou Project Office respectively, 20.50% from Guangzhou Construction Group Co. Ltd, 19.25% are from China Railway Construction Corporation while the remaining 18.41% are from China Communications Construction Company. This implies that most of the respondents are males who falls between 35 and 44 years of age and are from China State Construction Engineering Corporation Guangzhou Branch and PowerChina Construction Group.

Hypotheses

Research Question One: What is the relationship between technology anxiety, social influence, computer self-efficacy and AI adoption among Chinese Construction Workers in Guangzhou, China

Table 2: PPMC summary showing relationship between technology anxiety and AI adoption among Chinese Construction Workers.

Variables	N	Mean	Std.dev	df	r	sig	r^2	P
AI Adoption	237	22.15	5.450	235	-.584**	.000	0.341	**<0.01**
Technology Anxiety		22.30	6.676					

Source: field survey

Table 2 revealed that there is a significant negative relationship between technology anxiety and AI adoption; r (235) = -.584, p<0.01, r^2= 0.341. Thus, the hypothesis is rejected. The table further revealed that increase in technology anxiety will lead to a decrease in the adoption of artificial intelligence. Co-efficient of determination (r^2 = 0.341) revealed that technology anxiety explained 34.1% variance in the adoption of artificial intelligence, i.e technology anxiety had large effect on adoption of artificial intelligence among Chinese Construction Workers in Guangzhou, China.

Hypothesis 2: There is no significant relationship between social influence and AI adoption among Chinese Construction Workers in Guangzhou, China

Table 3: PPMC summary showing relationship between social influence and adoption of artificial intelligence.

Variables	N	Mean	Std.Dev	df	r	sig	P
Adoption of artificial intelligence	237	22.15	5.450	235	.072	.270	>0.05
Social influence		2.42	1.100				

Source: field survey

Table 3 revealed that there is no significant relationship between social influence and adoption of artificial intelligence; r (235) = .072, p>0.05. This revealed that there is no significant relationship between social influence and adoption of artificial intelligence among Chinese Construction Workers in Guangzhou, China. As a result of this, the hypothesis is accepted.

Hypothesis 3: there is no significant relationship between computer self-efficacy and AI adoption among Chinese Construction Workers in Guangzhou, China.

Table 4: PPMC summary showing relationship between computer self-efficacy and adoption of artificial intelligence.

Variables	N	Mean	Std.Dev	df	r	sig	r^2	P
Adoption of artificial intelligence	237	22.15	5.450	235	.349	.000	0.122	<0.05
Computer self-efficacy		2.45	0.860					

Source: field survey

Table 4 revealed that there is a significant relationship between computer self-efficacy and adoption of artificial intelligence; r (235) = .349, P<0.05. Thus, the hypothesis is rejected. The table further revealed that increase in computer self-efficacy will lead to an increase in the adoption of artificial intelligence. Co-efficient of determination (r^2=0.122) revealed that computer self-efficacy explained 12.2% variance in the adoption of artificial intelligence, i.e computer self-efficacy had large effect on adoption of artificial intelligence among Chinese Construction Workers in Guangzhou, China.

Hypothesis 4: There is no joint contribution of technology anxiety, social influence and computer self-efficacy to the adoption of artificial intelligence among Chinese Construction Workers in Guangzhou, China.

Table 5: Summary of regression for the joint contribution of technology anxiety, social influence and computer self-efficacy to the adoption of artificial intelligence.

R =.689[a] R Square =.475 Adjusted R square =.464 Std. Error =3.99165						
Model		**Sum of Squares**	**Df**	**Mean Square**	**F**	**Sig.**
1	Regression	3329.950	3	1109.983	70.270	.000[b]
	Residual	3680.582	233	15.796		
	Total	7010.532	236			

Source: field survey

Table 5 reveals significant joint contribution of technology anxiety, social influence, computer self-efficacy, perceived stigmatization and social isolation to the adoption of artificial intelligence. The result yielded a co-efficient of multiple regressions R = 0.689 and multiple R-square = 0. 475. This suggests that the five factors when combined accounted for 46.4% (Adj.R^2= .464) variance in the prediction of HIV status disclosure. The other factors accounting for the remaining variance are beyond the scope of this study. The ANOVA result from the regression analysis shows that there was a significant effect of technology anxiety, social influence and computer self-efficacy to the adoption of artificial intelligence, $F_{(3, 233)} = 70.270$, $P<0.05$.

Hypothesis 5: What is the relative contribution of each of technology anxiety, social influence, computer self-efficacy, perceived stigmatization and social isolation to the adoption of artificial intelligence among Chinese Construction Workers in Guangzhou, China, Oyo state?

Table 6: Summary of regression for the relative contributions of each of technology anxiety, social influence and computer self-efficacy to the adoption of artificial intelligence.

Models		**Unstandardized Coefficients**		**Standardized Coefficients**	**T**	**Sig.**
		B	**Std. Error**	**Beta**		
1.	(Constant)	9.327	1.457		6.403	.000
	Technology Anxiety	1.777	.242	-.436	-7.330	.000
	Social influence	.184	.244	.037	.754	.451
	Computer Self-Efficacy	1.316	.134	.238	9.810	.000

Source: field survey

Table 6 shows that two (technology anxiety and computer self-efficacy) out of the three predictive factors are potent predictors of AI adoption. The most potent factor was technology anxiety (β = -.436, t = -7,330, P<0.05) and lastly computer self-efficacy (β = .238, t=9.810, P<0.01). This implies that technology anxiety and computer self-efficacy decreased and increases the tendency of AI Adoption by 43.6% and 23.8% respectively.

Discussion of Findings

Hypothesis one investigated the relationship between technology anxiety and AI adoption by the Chinese construction workers in Guangzhou, China. As shown in Table 2, technology anxiety was found to be statistically significantly negatively correlated with AI adoption (r=-0.584, p< 0.01). This shows that the levels of technology anxiety are high in the case of less AI adoption. The r2 (= 0.341) also indicates that the technology anxiety can explain 34.1 percent of the variance in the adoption of AI. The null hypothesis which states that there is no significant relationship between technology anxiety and AI adoption is therefore rejected. This finding is also correlative to the existing empirical studies which have consistently pointed to technology anxiety as a significant psychological inhibitor of the adoption of new technologies. An example is that, according to Di Giacomo et al., (2019), those subjected to increased anxiety levels with regard to digital technologies are known to have avoidance behaviors, less confidence, and less motivation to use the technologies. Chang et al., (2025) also indicate that high tech anxiety significantly inhibits digital innovation acceptance in the work environment.

Recent research, including that of Keung and So (2025), verifies that AI-related anxiety, which is caused by the fear of being replaced by an AI, the misuse of the data, or being discriminated against by the algorithm, has a negative effect on the trust and perceived usefulness of AI systems in people. This trend is reflected in the existing results, with claimants of anxiety related to the use of AI systems potentially feeling that these tools are complex, threatening, or not within their competence skills, which reduces their readiness to use them. Besides, the effect size ($r^2 = 0.341$) is quite high, highlighting the fact that technology anxiety is a strong deterrent to the introduction of AI in this regard. This is similar to Wang et al., (2025), who noted that the feeling of anxiety when it comes to AI at work negatively affects acceptance without properly balanced exposure and organizational support. Since construction work in Guangzhou commonly implies manual work and little technological training, this anxiety may be supported by the fear of losing a job or being too digitally illiterate, further confirming the conclusion that technology anxiety is a determining factor of AI implementation behavior in employees in the developing industrial environment.

Hypothesis two examined the relationship between social influence and AI adoption among Chinese construction workers in Guangzhou, China. Table 3 above shows that there was no statistically significant correlation between social influence and AI adoption ($r = 0.072$, $p<0.05$). Based on this, the null hypothesis is accepted. This result indicates that the views or the actions of colleagues, managers, or the work mates have no meaningful impact in influencing the personal decision to use AI tools among the participants in the sample population. This finding is opposed to forecasts of Glass and Li (2010), which assumes that social influence is a salient factor of technology adoption, especially when individuals feel the need to be influenced by others in the environment to use a particular system. However, the outcome slightly concurs with empirical findings, which show that the impact of social influence differs depending on organizational structure and cultural influence. Indicatively, Chen and Lee (2025) discovered that the social influence is a major predictor of AI adoption in the corporate world characterized by high levels of structure where managerial support and peer pressure direct behavior. In contrast, social influence can be weaker in those sectors that are individualized (e.g., construction) and performance-oriented (e.g., task-oriented) in nature. Employees in this industry might make adoption choices on more individual-perceived usefulness and ease of use than social or normative influence.

Besides, the fact that the relationship is not significant may also be explained by the fact that AI implementation in the construction industry is still at its infancy. As Wang et al., (2021) observed, the social influence gets strong only when a technology has reached a diffusion threshold i.e. when sufficient numbers of people in the community already use it, thus, forming a bandwagon effect. The use of AI in construction settings is still a relatively new phenomenon, which means that the social norms of its usage have not yet been well-established to alter the behavior. Therefore, the discovery suggests that the use of AI by the Chinese construction workers is not socially reinforced but rather encouraged at an individual level. The organizational approaches to encourage adoption should be focused on the enhancement of the skills and personal confidence instead of the use of the peer pressure or managerial persuasion.

Hypothesis three investigated the relationship between computer self-efficacy and the adoption of AI by Chinese construction workers in Guangzhou, China. Table 4 demonstrates that there is a significant positive correlation between computer self-efficacy and AI adoption ($r= -0.349$, $p<0.05$), which explains 12.2% variance in adoption behavior. In this regard, the null hypothesis that there is no significant correlation between the computer self-efficacy and the adoption of AI was rejected. This finding goes in line with a large number of empirical studies that indicate that self-efficacy is core in technology acceptance. Bandura (1997) has determined that the motivational drive and persistence of individuals in the use of certain technologies is influenced by belief in their ability to undertake the technological activities. Similarly, Tseng (2025) have found that people with greater computer self-efficacy experience that digital tools will be more user-friendly and, as a result, increase their intention of adopting them.

Similar results were discovered by Montag, Zhang and Yu (2025), who concluded that self-efficacy in dealing with AI interfaces is a good predictor of willingness to use generative AI platforms. The results of the current research showed that the higher building workers were in their confidence about their abilities in computing, the more likely they were to test AI-driven applications, including automated project monitoring systems or risk prediction systems. This finding also corresponds to the empirical data that self-efficacy mediates the negative effect of technology anxiety- i.e. confident users have lower levels of technology anxiety about the complexity of technology (An et al., 2024). Thus, the positive correlation in this case is very high, which means that the development of computer self-efficacy may be regarded as an essential intervention to increase the rates of the AI adoption in the construction industry. A training program that focuses on learning through hands on, exposure and mastery through experience, might help to significantly alleviate anxiety, and increase confidence, which would increase acceptance levels.

Hypotheses four and five tested the joint and relative contributions of technology anxiety, social influence and computer self-efficacy to predicting the adoption of AI among Chinese construction workers in Guangzhou, China. The regression model of the Table 5 shows that there is a significant predictive value of technology anxiety, social influence, and computer self-efficacy ($R=.689$, R^2

=.475, $F_{(3,233)}$ = 70.270, p<.05). Therefore, these variables are said to account 47.5% of the variance in AI adoption between the respondents and the remaining 52.5% can be explained by variables outside the model.

However, the multivariate findings in Table 6 indicate that; only technology anxiety (β=-.436, p<.05) and computer self-efficacy (β =.238, p<.01) was significant independent predictors of the adoption of AI and social influence (β=.037, p>.05) was not. The result of this trend validates the previous assumption that affective (anxiety) and cognitive (self-efficacy) constructs have a stronger influence on AI adoption than normative or social pressures in this particular scenario.

The negative influence of technology anxiety is the most common, which corresponds to the previous empirical research findings by Anderson (2011), which have highlighted that even in high-technological industries, the adoption process is hindered by the negative affective response to technology, in particular through the fear of becoming obsolete and not knowing what is in store. On the contrary, the positive impact of computer self-efficacy supports the self- efficacy theory and results of Bandura (1997) and Holden and Karsh (2010), which state that the outcome of believing that one is capable of a specific task increases one's chances of employing technology.

The insignificance of the social influence is in line with the previous correlational data and could indicate the relative low level of peer-induced technological diffusion in the context of construction work settings as Lu et al., (2025) emphasizes. Together, the combined model highlights that, despite the impact of organizational culture and peer norms to the contextual environment, personal psychological orientations of the worker- especially anxiety and efficacy- have an ultimate effect on the adoption or rejection of AI technologies.

The results determine the importance of the technology anxiety and computer self-efficacy as the key psychological foretellers of AI acceptance among Chinese construction workers. High levels of anxiety reduce propensity to adopt and strong levels of self-efficacy increase it. Social influence, though having an abstractly relevant impact, carries a fringe impact in this professional environment. The cumulative explanatory rate of these variables is about 47.5% of the variance in the adoption of AI behaviour, which means that future interventions to promote AI adoption should focus on reducing anxiety and stimulating digital competence by organizing training, providing clear communication, and supportive organizational attitudes.

Conclusion

The study made the following conclusion: technology anxiety and computer self-efficacy can be seen as important predictors of AI adoption among construction workers in Guangzhou, China. Employees with higher anxiety levels had lesser intentions to embrace AI, and employees with high computer self-efficacy were more willing to use AI devices. On the other hand, the social influence was not a powerful factor, which points to the fact that the use of AI in this scenario is more one-on-one than a societal phenomenon. Based on this, the readiness of employees to welcome AI is dependent on their emotional and cognitive readiness, and not on the societal expectations. As a result, the strategies aimed at the adoption of AI must focus on eliminating the technological anxiety and increasing the level of digital self-confidence of the workers.

Recommendations

Judging by the empirical evidence, the following recommendations are put forward:

1. The construction companies are advised to introduce frequent, practical AI training to enhance the competency and self-efficacy of the workers using AI tools.
2. The management must create a friendly learning atmosphere whereby errors in AI use are accepted as part and parcel of the learning process and must provide counselling and mentorship programmes in order to soothe fears related to new technologies.
3. The modules of training need to focus on the practical experience and demonstrations, and not just theory, which will strengthen belief in the use of AI.
4. Social influence was not of significant importance, yet the development of teamwork and the openness to discuss the use of AI can create an uptake indirectly.
5. Governmental agencies and regulators in the industry should develop policies of AI integration, which anticipate human-oriented incorporation, web literacy, and incorporation of workers in decision-making.
6. Future researchers are advised to repeat such a research in other Chinese provinces or other national settings to ascertain cultural and industrial differences in adoption patterns of AI among workers in the construction industry, which would in turn improve the overall external validity of the results.

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