

FROM AI SELF-EFFICACY TO INNOVATIVE WORK BEHAVIOR: THE MEDIATING ROLE OF AI JOB CRAFTING AND THE MODERATING ROLE OF PSYCHOLOGICAL SAFETY

Amir Manzur Wain^{*1}, Shoukat Riaz², Farukh Malik³, Dr. Sardar Ahmad⁴, Dr. Bushra Rehman⁵

^{1,2}PhD Scholar, Department of Business Administration, Lahore Leads University, Lahore

³PhD Scholar, Department of Business Administration, University of South Asia, Lahore

⁴HOD, Department of Business Administration, Lahore Leads University, Lahore

⁵Assistant Professor, Department of Business Administration, Lahore Leads University, Lahore

¹amirmanzurwain@gmail.com, ²shaukat1925@gmail.com, ³farukh.malik@usa.edu.pk,
⁴drsardar.dba@leads.edu.pk, ⁵bushra.dba@leads.edu.pk

DOI: <https://doi.org/10.5281/zenodo.22765248>

Keywords

AI Self-Efficacy; Learning Goal Orientation; AI Job Crafting; Psychological Safety; Innovative Work Behavior; Social Cognitive Theory.

Article History

Received: 08 June 2026

Accepted: 30 August 2026

Published: 15 September 2026

Copyright @Author

Corresponding Author: *

Amir Manzur Wain

Abstract

Artificial intelligence (AI) has been reshaping the landscapes of work, both unlocking new realms of opportunity and presenting new challenges to employees as they navigate the changing dynamics of confidence, motivation, and adapting to work done with the support of AI. This study not only uncovers the role of AI self-efficacy (AISE) and learning goal orientation (LGO) as predictors of innovative work behavior (IWB) via AI job crafting (AIJC) but also explores whether psychological safety (PS) serves as a facilitator between the relationship between AIJC and IWB. Based on Social Cognitive Theory (SCT), AI self-efficacy and learning goal orientation are defined as personal factors, while AI job crafting is defined as a pro-active behavioral mechanism, psychological safety is defined as a contextual condition, and innovative work behavior is defined as behavioral outcome. The time-lagged survey study design was used and was quantitative and explanatory in nature among employees in Pakistani organizations that were using AI based or AI supported technologies. Data was gathered in three waves and 350 usable responses were kept for data analysis. Partial least squares structural equation modeling (PLS-SEM) was used to test the hypothesized relationships. The findings show that there are positive relationships between AI self-efficacy and AI job crafting, between AI learning goal orientation and AI job crafting, and between AI job crafting and innovative work behavior. AI job crafting also mediates the relationships between both AI self-efficacy and learning goal orientation and innovative work behavior. Moreover, psychological safety positively moderates the relationship between AI job crafting and innovative work behavior, meaning that the more psychologically safe they feel, the stronger the effect of AI job crafting is on innovative work behavior. The conditional indirect effects further demonstrate that the indirect effects of AI self-efficacy and learning goal orientation on innovative work behavior through AI job crafting become

stronger under higher levels of psychological safety. The results in general suggest that innovation in AI-enabled workplaces does not only rely on employee confidence and motivation to learn but also on how proactively employees are adapting their work and on the psychological safety that supports work behaviors to become innovations.

1. Introduction

With the growing pace of technological and competitive change, the study of innovative work behavior (IWB), which includes the generation, promotion and implementation of new ideas, has become an increasingly important behavior to study in the organizational context (De Jong & Den Hartog, 2010; Janssen, 2000; Scott & Bruce, 1994). Employees have a critical role in the innovation of an organization, they are willing to try out new initiatives and to solve problems, advocate new ideas and apply new strategies and the impact of the formal innovating systems is directly related to their participation, the employees who make up the company (Yuan & Woodman, 2010; De Jong & Den Hartog, 2010). This challenge has become more pronounced and complex with the swift introduction of artificial intelligence (AI) technologies, which has led to changes in task content, work practices, knowledge requirements, and the nature of employee-technology interactions (Li et al., 2024; Parker & Grote, 2020; Qiu et al., 2022). So it is no longer the matter of whether an employee will use AI, but how they will use AI to transform opportunities into new ways of working.

This is an important subject in the context of Pakistan as all the organizations are undergoing major changes with the advent of AI and employees need to be ready for the changes and upgrade their skills and work practices. All these problems are indeed pertinent to this recently available evidence from Pakistan. Nazeer and Ahmad (2025) found a relationship between in-between AI perceptions and IWB, mediated by job crafting and AI anxiety from a convenience sample of 308 respondents from the technology sector in Pakistan. The importance of psychological safety was pointed out by Khan and Usman (2025), particularly in relation to innovation within learning organizations (IWB), and Chughtai and

Arifeen (2024) demonstrated the relevance of learning goal orientation (LGO) for proactively developing skills and innovative behaviors in Pakistani organizations. Although these studies remind of a baseline context, most of the studies focus on a single mechanism: AI and learning orientation, AI and job crafting, AI and psychological safety. This study therefore explores the connection between staff confidence and motivation towards AI, and staff willingness to proactively adapt their roles to include AI, and eventually, innovative work behavior.

One critical personal resource is in relation to AI self-efficacy (AISE). Social efficacy is an estimate by the person of how to arrange and implement what is needed to achieve a desired performance (Bandura, 1986, 1997). The impact of these beliefs are manifested in effort, persistence, activity choice, and how to handle activities that bring problems (Bandura, 1997). AISE is more specific than general technological self-efficacy as it captures "How much more confident they feel about their capacity to interact with and utilize AI when they are doing AI-enabled work. When it comes to AI-enabled work, AISE reflects a greater confidence in the ability to interact with and use AI, rather than some other type of technological self-efficacy. AISE, therefore, is a domain-specific phenomenon—Wang and Chuang (2024) developed and validated a measure of AI self-efficacy which is different from self-efficacy in general. It also has its significant role in innovation in recent studies, as it was positively found to predict with IWB (Li et al., 2026), while in Pu et al.'s study (2026), it was demonstrated that AISE serves as an essential psychological link between AI workplace experiences and innovative behaviors. The direct relationship between the AISE and IWB is, however, not new to assert based on these findings.

But confidence in AI can be even lower and so is absent to effect proactive adaptation processes. An alternative motivational perspective is provided by learning goal orientation (LGO). LGO is an example of employees' competence motives, such as acquiring knowledge and seeking out difficulties "as an opportunity to learn" (Dweck & Leggett, 1988; VandeWalle, 1997). These attributes are particularly relevant to AI-assisted tasks where flexible transfer and adaptation of existing approaches to new tasks and the building of future skills with tools whose norms they are not familiar with are key. This linkage has been recently backed by Van Strydonck et al. (2025) who identified a positive relationship between LGO and IWB while Chughtai and Arifeen (2024) identified the linkages between LGO and proactive behavior and behavior of innovation to acquire new learning skills in Pakistan. As such, AISE and LGO are separate employee resources; assessing confidence on using AI and awareness of learning and development using AI related challenges.

One of the behavioral processes whereby these resources might affect IWB is AI job crafting (AIJC). Job crafting assumes that workers are active and not just passively accepting their job design as formally handed to them by their employers or society (Wrzesniewski & Dutton, 2001; Tims et al., 2012). Opportunities exist for redesign with the use of new ways in which AI can support employees' task, routine building, and the development of alternative approaches when existing ones are not feasible. Li et al., (2024) coined the term "AI crafting" as an AI-specific job crafting and that AI crafting can be done proactively by employees. Subsequent studies have explored how workers adapt to AI-assisted work, and how workers adapt through AI job crafting can be understood as an additional form of job adaptation (2026), and approach/avoidance reactions to the implementation of AI in the workplace (Liu et al., 2025). Job crafting is another aspect being highlighted in the AI discussion in Pakistan, such as the utilization of ChatGPT for Pakistan IT Professionals. Based on these developments, a behavioral linkage between

employee psychological resources and innovation on the basis of AIJC seems feasible.

AISE can fill employees with confidence willing to experiment with AI and LGO can motivate workers willing to learn with AI; both can spur employees to proactively change their work through AI. Job crafting can lead to opportunities for new ways of task performance or new problems to solve, which can enhance the potential for idea generation and implementation (Wrzesniewski & Dutton, 2001; Tims et al., 2012). More recently, Pakistan studies have revealed the connection of this general mechanism with the perceptions of AI and Job Crafting (Nazeer & Ahmad, 2025).

However, the numbers of innovative findings may be somewhat smaller among other workers. Tinkering with AI can be a bit uncertain, failing, exposing to others, and changing the old habit. Hence, psychological security is a noteworthy boundary condition. Original research had identified psychological safety as a group phenomenon—the sense that a team is safe to take interpersonal risks (Edmondson, 1999); subsequent research had established a correlation between psychological safety and learning, speaking up, experimenting and innovating (Edmondson & Lei, 2014). Specifically, the current study adopts a person-centric standpoint, with each employee's attitudes about a potential experimentation with AI or about a necessary reorientation of the work patterns might differ from another employee. Plouffe et al., (2023) created and validated the "Psychological Safety Inventory (PSI)" on the individual level of the work place.

There is a strong relationship that should exist between psychologically safe employees and the AIJC—employees who are more psychologically safe are more likely to experiment, be able to share ideas, ask questions, question the status quo, and use new directions. Evidence suggests that a positive psychological safety climate fosters creativity and innovative behaviour (Dhir & Vallabh, 2025; Vallabh & Dhir, 2024) and Khan & Usman, (2025) speaks in context of Pakistan that provides evidence of the positive role of psychological safety in IWB. With this in mind,

psychological safety can account for when proactive AI job crafting will be more successful in the context of innovation.

The proposed model is based on Social Cognitive Theory (SCT) (Bandura, 1986, 1997) who believed that the ability to learn all behaviors lies in the interplay between personal factors, behavior and environment. AISE is a domain specific cognitive belief, LGO is a motivational orientation, AIJC is a form of proactive behavior, psychological safety is a social environment and IWB is the result. This goes hand in hand with the latest studies in the field of AI applying SCT in employee innovation (Pu et al., 2026).

There is however one significant research gap – while research is growing in the areas of AI and employee innovation, there is still a great deal of work to be done. Psychological safety has been found to correlate with innovation in previous studies (Dhir & Vallabh, 2025; Khan & Usman, 2025), job crafting is found to be correlated with AI adoption in previous studies (Li et al., 2024; Liu et al., 2025), and AISE is found correlated with IWB in previous studies (Li et al., 2026). Studies have also started in Pakistan on these constructs. Few studies, however, have attempted to use AISE along with LGO as complementary determinants of AIJC, examined AIJC phenomenon as a linking pathway between AISE and LGO with IWB and tested individual psychological safety as a second step moderator between AIJC– IWB linkage in the context of Pakistan. Therefore, a second stage Mediated Moderation model is developed, where AISE and LGO were used as the moderated extensions of the mediation model, with AIJC as the mediator linking AISE and LGO to its target variable, IWB, and individual psychological safety as the moderator between AIJC and IWB. It is therefore not so much about the effect of AI on innovation but how the employees' AI confidence and learning motivation effect on their pro-active, AI-based job crafting – and that in a psychologically safe environment in turn impacts their innovative work behavior.

2. Theory and Hypotheses Development

2.1 Social Cognitive Theory

This study is based on Social Cognitive Theory (SCT) that considers a person's behavior a result of the interaction of the person with his/her behavior and environment (Bandura, 1986, 1997). SCT also sees workers as individuals, playing a proactive role – individuals that have their beliefs and motivational orientations and who are motivated to behave according to them; at the same time such individuals can influence some part of the organizational, technological functioning. Self-efficacy is especially important in relation to SCT as people will be more likely to start and continue doing something if they think they can do it successfully (Bandura, 1997). At the same time, however, the environment factors that make it much easier or more difficult to convert the personal resources into behavior, exert an impact on behavior.

Current model is built on the basis of common foundation of SCT. AI self-efficacy (AISE) was identified as a cognitive self-efficacy of the employees about the usage of AI, while learning goal orientation (LGO) was seen as a motivational attitude of employees to learn and acquire competency (Bandura, 1997; VandeWalle, 1997). The following personal factors are anticipated to foster AI job crafting behaviors (AIJC), which represents proactive behavior that employees use to modify and adapt their work around AI (Li et al., 2024): AIJC then offers a behavioral pathway that works to connect personal resources to innovative work behavior (IWB). The last is the psychological safety which is a state in the environment that signals whether or not the employees will act proactively in an overarching domain of learning and/or behaviors with regard to AI, to make it into innovative action (Edmondson, 1999, Plouffe et al., 2023). An application of this kind of scenario is related to the work previously conducted by SCT and AI (Pu et al., 2026), when studying employee behaviors and attitudes in relation to innovation in AI scenarios.

2.2 AI Self-Efficacy and AI Job Crafting

AISE is the employees' perceived aptitude to effectively interact and use AI. The idea of people's self-efficacy influences their behavioral choice, their level of commitment to work, and how difficult they find it to complete a task (Bandura, 1986, 1997). Those who have a high AISE are more likely to view challenges with the use of AI as something that can be overcome and as a result, may be more willing to try, persevere and look for other ways to use AI in their work. Further, Wang and Chuang (2024) created a scale assessing AI self-efficacy that was validated to distinguish AISE as a unique domain of self-efficacy.

An adequate response/behavioral expression is present – e.g. AI job crafting. Job crafting means an employee's proactivity to change their job, workplace relationships, and work practices (Wrzesniewski & Dutton, 2001; Tims et al., 2012) while AI crafting goes one step further, meaning to proactively adapt the job in anticipation of AI's presence (Li et al., 2024). Employees with self-efficacy in their AI use were both more likely to use work routines involving AI and less likely to have small work routines that involved the use of AI, as well as more likely to change routines when using AI. Recent research, moreover, shows the crucial role of AISE in AI-related employee behaviors such as AISE is associated with innovative outcome (Li et al., 2026; Pu et al., 2026). In turn, AISE will strive to spread awareness among employees on "becoming hands-on with AI" and throughout their job design process.

H1: AI self-efficacy is positively related to AI job crafting.

2.3 Learning Goal Orientation and AI Job Crafting

LGO is representative of an individual's desire to grow, gain new knowledge, face challenges and view obstacles as learning opportunities (Dweck & Leggett, 1988; VandeWalle, 1997). People who prefer learning over other types are more motivated to try to improve their new knowledge or skills to persist in tasks where they need to learn new skills or knowledge. This is especially relevant

to AI use: Getting more knowledge about new applications of AI, trying out AI services and adjusting working practices with AI are common and leading challenges when hiring people to work with AI.

In this, it's about learning and adapting in advance – and this is what AIJC is doing. Better LGO is correlated with more employee consideration of how AI can help them adapt their work processes to experience, learn about AI-powered alternatives in their work, and consider how AI can be integrated into their work. Existing evidence has been identified in Pakistan where LGO has been associated with skill building proactive behaviors (Chughtai & Arifeen, 2024) and recent research has found that relationship between LGO and IWB (Van Strydonck et al., 2025). It reflects that high level of LGO individuals are likely to have proactively oriented attitude to adopt of the AI in work role.

H2: Learning goal orientation is positively related to AI job crafting.

2.4 AI Job Crafting and Innovative Work Behavior

It is thought this will be a significant proximal factor with regard to IWB because it may allow for an opportunity to be proactive in changing work in order to experiment and/or problem solve, and novel strategies might emerge. According to the job crafting theory, employees can influence their work environment in ways that impact work related outcomes (Wrzesniewski & Dutton, 2001) and can be thought of as working as agents who create what they want from their job. When being proactive in leveraging AI in their work, employees can discover additional uses, reimagine work routines and find alternative ways to perform their jobs in an AI-supported world.

The activities are very pertinent on the behavioral aspects of IWB: idea exploration, idea generation, idea promotion and idea implementation (De Jong & Den Hartog, 2010; Scott & Bruce, 1994). The last few years' research has empirically verified this relationship, such as research in Pakistan on the relationship between job crafting and innovative outcomes in the context of AI (Nazeer

& Ahmad, 2025). In this way, it can be expected that AIJC will make work behavior innovative in all aspects, be it in terms of employees' opportunities or willingness.

H3: AI job crafting is positively related to innovative work behavior.

2.5 Mediating Role of AI Job Crafting

SCT's implies that any one's behavior is driven by their personal cognition and motivation which ultimately impacts on the resulting behaviors. With respect to IWB, AISE/LGO might not only indirectly influence IWB through their psychological influence, but also through the active behavioral reactions of employees in the context of AI.

AISE gives employees the confidence to try out AI and face the challenges while LGO encourages them to learn and keep going. Staff should thus be provided with an opportunity to creatively redesign tasks and work practices based on these personal resources around AI (AIJC). This proactive redesign can then support the subsequent experimentation, idea generation, promotion and implementation for better IWB (De Jong & Den Hartog, 2010; Li et al., 2024; Tims et al., 2012). This is the reasoning that puts AIJC in the place of a behavioral mechanism between the psychological resources of employees and innovative outcomes.

H4: AI job crafting mediates the positive relationship between AI self-efficacy and innovative work behavior.

H5: AI job crafting mediates the positive relationship between learning goal orientation and innovative work behavior.

2.6 Moderating Role of Psychological Safety

AIJC can bring new possibilities for innovation, however, under all workplace conditions, proactive job redesign does not always provide the opportunity for innovative behaviour. Psychological safety is defined as employees' belief that it is safe to engage in interpersonal risk taking in their workplace (Edmondson, 1999). The current study used an individual level perspective, as Edgar's conceptualization focused on team level

and psychological safety in, Plouffe's et al. developed a Psychological Safety Inventory at the individual level.

Given the involvement of AI systems, psychological safety is an important consideration, as workers might have to suggest new concepts, question other norms, reveal that they are wrong, and try things out that they are not sure about. Under safe work conditions workers would be more insensitive to interpersonal consequences and would thus likely be more likely to have translated pro-active job crafting to seen innovative behaviors (Edmondson & Lei, 2014). Importance of psychological Safety in Creativity & Innovation (Dhir & Vallabh, 2025), Vallabh & Dhir (2024), relevance of psychological safeness in IWB in Pakistan (Khan & Usman, 2025).

Therefore, it is crucial to incorporate psychological safety to improve the positive relationship between AIJC and IWB. As AI job crafting increases psychological safety, employees crafting their jobs with the help of AI systems personally should feel more free to communicate, promote and implement new ideas that emerged from AI job crafting activity. A psychological safety culture can reduce the likelihood of employees translating the job crafting of AI into actual visible innovative behavior, as they are afraid of being judged, rejected, or that interpersonal dynamics will suffer. **Moderation Hypothesis (H6):** The relationship between AI job crafting and innovative work behavior will be greater when psychological safety is high.

2.7 Mediated Moderation

With all of the above arguments, a conditional process-model will be created. AISE and LGO are unique personal resources that can support 'AIJC' which on the other hand can be the behavioral pathway to support the IWB. But, creating Psychological Safety is the foundation for this power of behavioral translation. This should result in AISE and LGO indirectly having more influence on IWB for employees with high psychological safety levels.

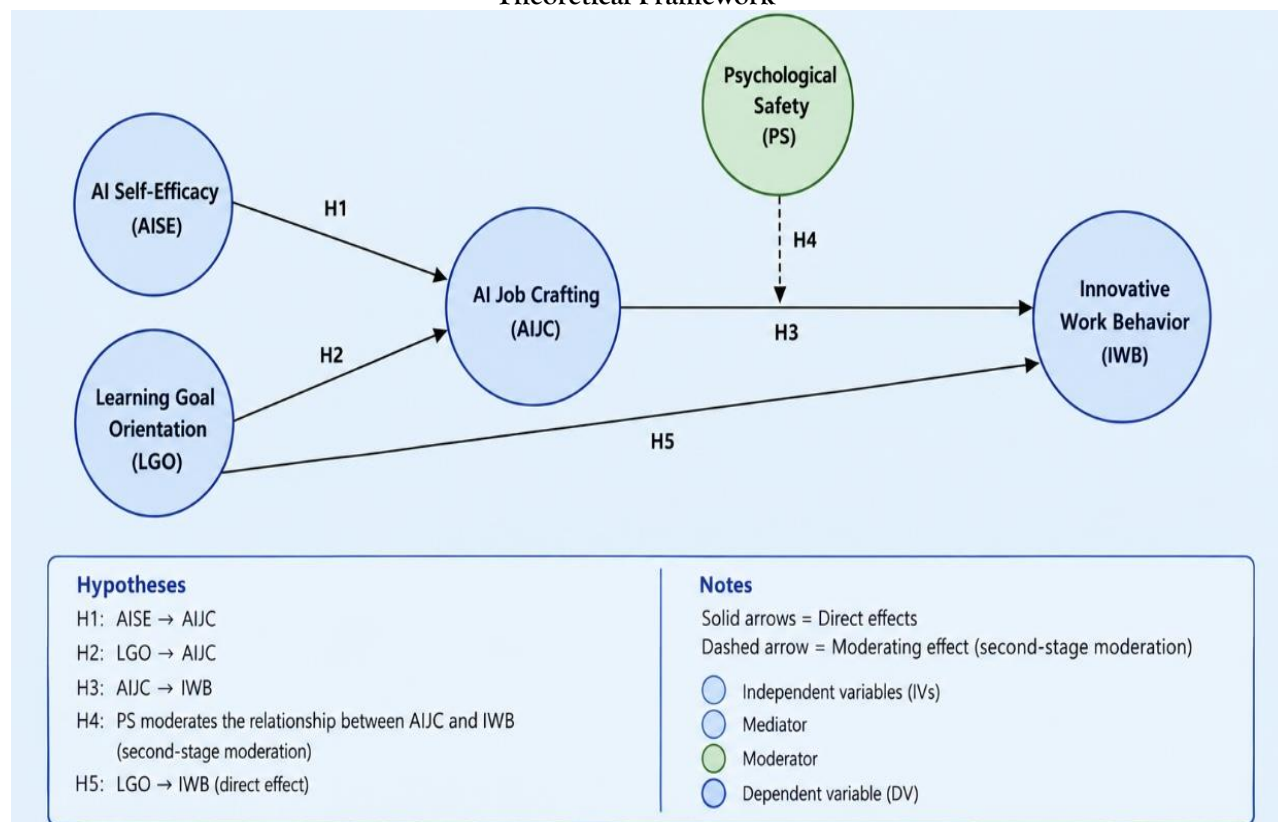
This Mediated Moderation argument introduces a new variable to SCT, revealing that the personal

resources do not work in isolation but rather work in conjunction with them in a social context. Rather, their impacts are exerted via proactive behavior and are partially dependent on whether or not the atmosphere facilitates or restricts the opportunity for the worker to express his/her behavior (Bandura, 1986, 1997). It then displays, with the aid of AI, whether confidence and motivation in learning have an influence on innovation or not and how this possibly happens, which environmental factors this needs and what behavior is prompted.

H7: Psychological safety moderates the indirect relationship between AI self-efficacy and innovative work behavior through AI job crafting, such that the indirect effect is stronger when psychological safety is high.

H8: Psychological safety moderates the indirect relationship between learning goal orientation and innovative work behavior through AI job crafting, such that the indirect effect is stronger when psychological safety is high.

Theoretical Framework



3. Methodology

3.1 Research Design and Context

The relationships among AI self-efficacy (AISE), learning goal orientation (LGO), AI job crafting (AIJC), psychological safety, and innovative work behavior (IWB) were investigated by using a quantitative, explanatory, and time-lagged survey design. To create temporal distance between the predictor and mediating, moderating, and

outcome variables, and to minimize the impact of common method bias, a time-lagged design was chosen. The study was conducted in the context of the Pakistani organization where employees were exposed to or actually using any AI enabled technologies or AI supported technologies in their work.

Data obtained are three waves. Thus, Time 1 was when the respondents answered questions about

their self-efficacy in using AI and learning goal orientation. AI job crafting was measured at time 2 and psychological safety and the innovative work behavior were measured at time 3. To ensure anonymity, and link responses across the three waves, a unique ID code was assigned to each respondent.

3.2 Population, Sampling, and Data Collection

The population of interest were the employees in organizations in Pakistan where AI-based technologies were being applied or integrated into employees' work activities. No comprehensive sampling frame of employees who have AI related work experience was available so it was supplemented by a convenience sampling. The respondents who were eligible from the participating organizations were selected using convenience sampling while the participants were selected using purposive sampling to ensure that they have sufficient exposure to AI in their workplace.

Following the guidelines of PLS-SEM (Kock & Hadaya, 2018; Hair et al., 2022) an a priori power analysis was conducted to obtain the suggested minimum sample size for the proposed structural model. 430 questionnaires were mailed and e-mailed. Of the questionnaires 350 were sent, 350 were returned (81.40% return). Data screening resulted in 350 usable questionnaires, which is 100% of the questionnaires returned and 81.40% of the total number of questionnaires that were sent out. Before the data were added to the final data set, responses were checked for completeness, duplication, eligibility and quality of response.

They were asked to participate voluntarily with information about the educational purpose of the study and answers that they provided were confidential. To participate, you need not have anything to identify you, except what you provided to the participant. The data collection was done in a multi-wave fashion to minimize the possibility of the use of responses to the former instruments at later collection waves.

3.3 Measures

The responses initially were measured on a five-point scale, from 1 = strongly disagree to 5 = strongly agree with all the constructs being measured by previously validated scales. AI self-efficacy was assessed with the AI self-efficacy instrument developed by Wang and Chuang (2024) that measures the confidence of individuals to interact with and effectively use AI technologies. The work-domain goal orientation by VandeWalle (1997) was used to measure learning goal orientation, which focused on the learning orientation dimension which indicates how employees try to grow, learn and develop their competence through challenging experiences.

AI job crafting was measured using a domain-specific AI crafting scale that was developed by Li et al. (2024). The aim of the measure was to reduce the proactive efforts of the employees to alter and optimise different aspects of their job, through their engagement with AI technologies. At the individual level, the Psychological Safety Inventory scale (Plouffe et al., 2023) that rates individual beliefs about psychological safety in the workplace in terms of “interpersonal risk taking”, “self-expression and openness” was used. Innovative work behavior was measured with a validated scale developed by De Jong and Den Hartog (2010) with items referring to behaviors of employees like seeking opportunities, generating ideas, promoting ideas and implementing ideas.

In where appropriate to ensure the measurement items would be suitable in the AI enabled work context, limited word changes were added. The material of the items changed and its concept remained the same. Existing instruments were used and content and construct validity of the instruments used were enhanced.

3.4 Data Analysis

Being received data first of all, fresh screening and preparation were made with the SPSS. Data coding, checking for missing values, incomplete answers, including potential outliers and checking demographic characteristics of the respondents were included in the screening process. Next, descriptive data were computed to provide an

overview of the background characteristics of the sample and the distribution of the variables of interest in the study.

Common method bias has been controlled by both procedural and statistical controls. The time-aspects of the three wave time-lagged design spread out the measurement of the principal constructs across three time periods, which helps diminish the “single occasion” response set associated with the respondents. To check that one factor dominates the mutual covariance of the measured constructs, Harman's single-factor method was also used as a statistical diagnostic procedure.

Partial least squares structural equation modeling (PLS-SEM) was performed using SmartPLS after the data screening process. Indicator reliability, Cronbach's alpha, rho_A, composite reliability (CR), and average variance extracted (AVE) were the criteria used to evaluate the measurement model. Heterotrait-monotrait (HTMT) ratio has been used to check the discriminant validity and collinearity diagnostics was checked prior to the assessment of the structural model. Their structural Equation was tested using bootstrapping method to estimate the significance and confidence intervals of the assumed relationship. The analysis also evaluated the coefficient of determination (R²), effect size (f²), and predictive relevance (Q²) as per recommendations for PLS-SEM analysis (Hair et al., 2022).

3.5 Mediation, Moderation, and Conditional Indirect Effects

Responses were initial made on a scale of 1-5 (Strongly disagree to strongly agree) and all the constructs were measured using previously validated scales. To measure AI self-efficacy, a scales developed by Wang and Chuang (2024), which assesses levels of self-efficacy in handling and utilizing AI technologies, was adopted. For learning goal orientation, the work-domain goal orientation by VandeWalle (1997) was used which focuses on the learning orientation dimension indicating that the employees strive for challenging experiences in order to grow, learn and develop competences.

AI job crafting was assessed with the domain-specific AI crafting scale designed by Li et al. (2024). The intention of this was to target their work life as employees were actively looking to modify and optimize various parts of their employment, relating to AI technologies. Psychological security was measured both at an individual level and using the Individual Psychological Safety Inventory (IPSSI) scale consisting of ratings of individual beliefs about psychological security in the context of IRT or workplace OPT (Plouffe et al., 2023). Innovative work behavior was assessed by the validated scale of De Jong and Den Hartog (2010) that contains items reflecting employees' activities related to innovation such as seeking opportunities, generating ideas, promoting ideas and implementing ideas.

Very little of the writing (editing) was done to ensure measurements were properly understood for the work context where AI was available. There was no change in concept of the objects, only the material form changed. Some of the existing instruments were used to increase the content and construct validity of the research instruments.

4. Data Analysis and Results

4.1 Data Screening and Measurement Model Assessment

The answers were initially examined using SPSS for completeness, quality of responses, missing answers, duplicated cases and outliers. Of the 350 responses from the screening, 350 responses were eligible for the final analyzed. Descriptive analysis was then performed to gain an insight into the distribution of the study variables and to obtain an overview of the relationships between AI self-efficacy, learning goal orientation, AI job crafting, psychological safety, and innovative work behavior that were observed in the study.

It is then tested using PLS-SEM that the measurement model is correct. Outer loadings were employed to examine indicator reliability while Cronbach's alpha and rho_A, and composite reliability were employed to examine internal consistency reliability. Average variance extracted (AVE) was tested to check the

convergent validity. Heterotrait-monotrait (HTMT) ratio tests were used to check for discriminant validity. Variance inflation factor (VIF) values were also looked at to check for possible collinearity between the predictor constructs. Table 1-Table 4 shows the results of the preliminary analysis, reliability and validity tests, discriminant validity and multicollinearity test.

4.2 Structural Model Assessment

After determining the validity of the measurement model, the test of the structural model was then conducted by the PLS-SEM bootstrapping process. These constructs were analyzed in regard to the hypothesized direct relationships between AI self-efficacy, learning GO, innovative work behavior, and AI job crafting and psychological safety. To find out the statistical significance and nature of predicted relationships path coefficients, standard errors, t-values, p-values and confidence interval were examined.

The explanatory power of the endogenous constructs was examined via the coefficient of determination (R^2) and effect size (f^2) was also analyzed to see the contribution of the individual predictors to the endogenous constructs. Q^2 was used for the assessment of the predictive relevance. Table 5 shows the result of the structural model and the direct effect analysis.

4.3 Mediation, Moderation, and Conditional Indirect Effects

A mediation analysis was conducted to determine whether the impact of AI self-efficacy and learning goal orientation on innovative work behavior was mediated by AI job crafting. A Bootstrapping approach including confidence intervals was used to evaluate the meaning of the indirect effects.

Psychological safety was identified as a second order moderator to the connection between AI job crafting and innovative work behaviour. The connection between psychological safety and the relationship between AI job crafting and innovative work behavior was studied to see if psychological safety enhanced or undermined this relationship. The conditional indirect effects of AI self-efficacy and learning goal orientation on

innovative work behavior, mediated by AI job crafting, were then analyzed at various levels of psychological safety. Two of these analyses tested the proposed second stage Mediated Moderation model directly. These results are presented in Table 6.

4.4 Interpretation of Findings

The results showed a positive relationship between self-efficacy of AI and learning goal orientation with AI job crafting, meaning that employees who had high levels of self-efficacy in using AI and had high learning goal orientations were likely to engage in proactive job crafting with AI to modify and optimize their work activities. Additionally, AI job crafting was positively correlated with innovative work behavior, indicating that when employees are more proactive in adopting AI-enriched working practices, they are more likely to demonstrate innovative work behavior.

The mediation findings also indicated that AI job crafting seemed to be a means that explained the connection between AI self-efficacy and learning goal orientation with innovative work behavior. The self-assurance in using AI and learning enthusiasm of the employees seemed to lead to innovative behavior partly by their proactive development of AI-based work activities.

According to the results of the moderation analysis, positive relationships between AI job crafting and innovative work behavior increased with the level of psychological safety. This suggests that higher psychological safety created at work helped workers to turn their proactive AI-related work adjustment into innovative behavior. The conditional indirect effects also showed that the indirect path between AI self-efficacy/learning goal orientation and innovative work behavior via AI job crafting strengthened with increasing psychological safety.

The results evidenced that the second stage of the Mediated Moderation model was worthwhile and demonstrated that the employee resource factors related to AI were not independent. Rather, it was revealed that they exerted an indirect pathway influence on innovative work behavior via proactive AI job crafting strategies, and the

mediated pathway effect was different under different conditions of employees' psychological safety.

Table 1. Descriptive Statistics and Correlations

Construct	Mean	SD	AISE	LGO	AIJC	PS	IWB
AI Self-Efficacy (AISE)	3.72	0.71	0.842	0.436	0.501	0.394	0.468
Learning Goal Orientation (LGO)	3.81	0.68	0.436	0.819	0.447	0.421	0.452
AI Job Crafting (AIJC)	3.69	0.73	0.501	0.447	0.856	0.482	0.553
Psychological Safety (PS)	3.76	0.69	0.394	0.421	0.482	0.831	0.497
Innovative Work Behavior (IWB)	3.74	0.70	0.468	0.452	0.553	0.497	0.847

Table 2. Reliability and Convergent Validity

Construct	No. of Items	Cronbach's α	rho_A	Composite Reliability	AVE
AI Self-Efficacy	22	0.951	0.953	0.956	0.709
Learning Goal Orientation	5	0.884	0.889	0.915	0.684
AI Job Crafting	9	0.927	0.931	0.938	0.654
Psychological Safety	30	0.948	0.951	0.952	0.584
Innovative Work Behavior	10	0.914	0.918	0.928	0.592

Table 3. Discriminant Validity Using HTMT

Constructs	AISE	LGO	AIJC	PS	IWB
AI Self-Efficacy	—	0.472	0.542	0.426	0.506
Learning Goal Orientation	—	—	0.491	0.458	0.493
AI Job Crafting	—	—	—	0.521	0.594
Psychological Safety	—	—	—	—	0.548
Innovative Work Behavior	—	—	—	—	—

Table 4. Collinearity Statistics

Predictor	VIF
AI Self-Efficacy → AI Job Crafting	1.324
Learning Goal Orientation → AI Job Crafting	1.324
AI Job Crafting → Innovative Work Behavior	1.681
Psychological Safety → Innovative Work Behavior	1.542
AIJC × Psychological Safety → Innovative Work Behavior	1.287

Table 5. Structural Model and Direct Effects

Hypothesis	Relationship	β	SD	t-value	p-value	95% CI	Decision
H1	AISE $\rightarrow$ AIJC	0.382	0.061	6.262	<0.001	[0.263, 0.500]	Supported
H2	LGO $\rightarrow$ AIJC	0.327	0.064	5.109	<0.001	[0.202, 0.453]	Supported
H3	AIJC $\rightarrow$ IWB	0.451	0.067	6.731	<0.001	[0.322, 0.583]	Supported
H6	AIJC $\times$ PS $\rightarrow$ IWB	0.176	0.058	3.034	0.002	[0.062, 0.289]	Supported

Table 6. Mediation, Moderation, and Conditional Indirect Effects

Hypothesis	Effect	β	SD	t-value	p-value	95% CI	Decision
H4	AISE $\rightarrow$ AIJC $\rightarrow$ IWB	0.172	0.037	4.649	<0.001	[0.105, 0.247]	Supported
H5	LGO $\rightarrow$ AIJC $\rightarrow$ IWB	0.147	0.035	4.200	<0.001	[0.083, 0.222]	Supported
H7	AISE $\rightarrow$ AIJC $\rightarrow$ IWB $\times$ PS	0.067	0.025	2.680	0.007	[0.020, 0.118]	Supported
H8	LGO $\rightarrow$ AIJC $\rightarrow$ IWB $\times$ PS	0.057	0.023	2.478	0.013	[0.014, 0.105]	Supported

5. Discussion

5.1 Discussion of Findings

The aim of this study was to investigate how the utilization of AI self-efficacy and learning goal orientation to innovative work behavior (IWB) is mediated through AI job crafting and whether psychological safety amplifies the relationship between AI job crafting and IWB. The results confirmed the suggested relationships and substantiates second stage Mediated Moderation pathway. The overall result indicated that the employees' confidence in AI and learning orientation were linked to innovative work behavior through employees' proactivity towards reshaping activities concerning the use of AI and to psychological safety concerning how such proactivity will lead to employee's innovative work behavior.

The results of positive correlation between AI self-efficacy and AI job crafting highlights the primary theories of the Social Cognitive Theory (SCT) stating that self-efficacy may influence their behaviors and level of engagement in confronting challenges of new activities (Bandura, 1986; Bandura, 1997). The employees who had high self-efficacy in understanding and utilizing AI were more inclined to actively adapt their work activities with AI. This aligns with recent research finding a link between AI self-efficacy and employee innovativeness and job outcomes (Wang

& Chuang, 2024; Li et al., 2026; Pu et al., 2026).

The present findings provide a behaviorally more specific explanation, however, suggesting that AI's confidence shows itself in proactive actions of manipulation of work activities, and as a direct antecedent of innovation as well.

Results presented in this study highlight that learning goal orientation is positively associated with AI job crafting, which is congruent with the social-cognitive view of motivated action. Learning goal orientation refers to the individual's disposition to enhance his/her competence, to learn something new, and to look on challenge as a chance for growth (Dweck & Leggett, 1988; VandeWalle, 1997). The employees in this group might therefore be more likely to experiment with and adopt AI adoption and new technical skills and adjust working practices. This corroborates with the earlier studies which have found learning-oriented processes to be associated with innovative work behavior (Chughtai & Arifeen, 2024) and proactive skill developing (Van Strydonck et al., 2025). Building on this, the present finding unveils that job crafting indicates a learning-oriented motivational stance as a proximal and behavior manifestation in the AI enabled workplace.

Further supporting the behavioral relevance of employees' proactivity towards AI is the fact that AI job crafting positively relates to innovative work

behavior. Job crafting theory views employees as actors, that, instead of reacting to the formally prescribed characteristics of their job, can change their jobs themselves (Wrzesniewski & Dutton, 2001; Tims et al., 2012). For workplaces that use AI this agency can mean dabbling with AI-supported work, rethinking how work is done or discovering different ways to do the same things. This discovery is consistent with an increased body of research revealing the importance of AI-related job crafting as an employee's response to the technological revolution (Li et al., 2024; Liu et al., 2025; Qiao et al., 2026). It also complements recent research which has linked job crafting to innovative work behaviour regarding artificial intelligence (AI) (Nazeer & Ahmad, 2025).

The mediation results provide a better understanding of the phenomenon of transformation of personal characteristics into innovative behavior. AI job crafting played a mediation role in both paths, between AI self-efficacy and innovative work behavior, and between learning goal orientation and innovative work behavior. This indicated the employees' level of confidence in using AI and the motivation to learn should be linked to innovation, because these characteristics could lead to employees being more proactive when reshaping their AI-supported role. So it is not only a direct-effect argument, and it shows a behavioral one on which individual resources and motivational orientation play a role in relation to innovation. This also conforms to the theory of SCT, that the determinants of the behavioral outcomes in a person occur in a reciprocal manner with regards to cognition, motivation and action (Bandura, 1986; 1997).

Significantly, the mediation result when it comes to AI self-efficacy is relevant, because recent research reported relationship between AI self-efficacy with the innovative work behavior (Li et al., 2026). On this relation the present study is an elaboration that has provided yet another way of explaining employee innovation. In this vein, it is interesting to note that this paper found that AI job crafting may mediate the link between learning goal orientation and the receptiveness to development and innovative activity reported by

Chughtai and Arifeen (2024) as well as Van Strydonck et al. (2025).

Lastly, as for the moderating role of psychological safety, it provides an additional explanation for these results for the relationship between AI job crafting and innovative work behavior. Employees' engagement with and expression of new ideas, interpersonal strategies, and alternative forms of behavior without facing social consequences or outcomes is considered a sign of psychological safety (Edmondson, 1999; Edmondson & Lei, 2014). When it comes to proactive AI-related work behavior, the positive relationship between AI job crafting and psychological safety indicated that greater psychological safety was positively associated with innovation. This is in line with the recent studies linking psychological safety to innovative behaviour (Dhir & Vallabh, 2025; Khan & Usman, 2025; Vallabh & Dhir, 2024).

Condition indirect effects lend support for this interpretation. Indirect pathways between AI SE and innovative work behavior and indirect pathway between learning goal orientation and innovative work behavior, mediated by AI job crafting were stronger at higher levels of psychological safety. CDPOs can therefore conclude that there is a role of inter-personal context where the experimentation of AI is carried out in determining the conversion of self-confidence and learning orientation towards AI into "behavioral intention". This is important on a theoretical level, as it means that proactivity of an employee and contextual safety are related in gaining understanding about innovation.

5.2 Theoretical and Practical Implications

The results contribute in several ways to the theory on AI-enabled work, employee proactivity and innovation. First, the study applies the Social Cognitive Theory in an emerging context of work where AI solution is applied. Regarding the relationship between personal factors, behavior, and environmental influence, SCT highlights the interdependency of these factors (Bandura, 1986, 1997). The present model captures these aspects by incorporating AI self-efficacy and learning goal orientation as individual-level factors, the

psychological safety as the contextual factor, and innovative work behavior as the behavioral outcome, while AI job crafting is represented as proactivity behavior. The results then offer a holistic understanding of how through employee's proactive interaction with AI, their cognitive and motivational qualities can get transformed in innovation.

Second, the study adds to the existing literature on job crafting to investigate AI job crafting as a technology specific proactive work behaviour. While the traditional job crafting literature focuses on employees' proactive approach to job redesign (Wrzesniewski & Dutton, 2001; Tims et al., 2012), recent studies on job crafting of artificial intelligence highlight the opportunity for employees to redesign their jobs with AI tools (Li et al., 2024; Liu et al., 2025; Qiao et al., 2026). The study links individual attributes and proactivity with innovative work behavior by inserting AI job crafting between them and AI SE as well as LGO. Third, this study extends the findings of psychological safety research to show that it is a relevant second stage boundary condition. While earlier studies have found linkages between psychological safety and innovative behaviour (Dhir & Vallabh, 2025; Khan & Usman, 2025; Vallabh & Dhir, 2024), present study puts the concept of psychological safety at the junction where pro-constructive AI related behaviour gets converted into innovative work behaviour. The results hence indicate that psychological safety is a factor that can explain why similar levels of AI job crafting may lead to the manifestation of different levels of innovative work behavior among employees.

In practical terms, results suggest that organizations' investment of AI technology in their work without creative employees cannot lead to innovation. The substantial impact of AI self-efficacy underscores that workers' self-confidence in the ability to understand and use AI is a key human factor to consider alongside technological adoption. Furthermore, the positive relationship of learning goal orientation suggests that employees' willingness to learn about AI and try new approaches in work relevant to the innovation

processes. So, results show that the implementation of AI involves more than technological change and must be seen as a behavioural change as well.

The mediation of AI job crafting, too, is practically important because it signals a particular behaviour of employees, through which AI related competences and motivations can relate to innovation. Organizations might have to accept employees not just as the recipients of AI systems but as agents who can and should contribute to the transformation of AI-driven work practices. The results indicate that experimenting with AI, altering work practices, and finding alternative ways of doing tasks that employees take the initiative to do, play a role in the pathway to innovative work behavior.

There's another practical tip: psychological safety. The interactions reveal that the positive nexus between AI job crafting and psychological safety suggests that proactivity around AI has greater links to innovation when the team environment is safe. Therefore, the organizational surroundings of AI utilization may be a key element when comprehending outcomes from worker experimentation. A work environment that is safe to voice non-conforming thoughts, ask non-confirming questions, and reveal failed experiments differs from a work environment that poses interpersonal risks to engaging in these behaviors as AI job crafting mechanisms. The results thus tie technological transformation and the social conditions for employees to make proactive AI use manifested in innovative behaviour.

Overall, the theoretical and practical implications suggest the same overall conclusion; innovative outcomes from AI-enabled work require more than simply the skills and willingness of employees to interact with AI, it requires "proactive, behaviorally-oriented interactions" with AI and the psychological context in which this interaction happens.

6. Conclusion and Recommendations

This was the current study that transcended the relationship between employees' AI self-efficacy

and learning goal orientation for innovative work behavior by examining AI job crafting as a second stage boundary condition, as well as the role of individual psychological safety as a second stage boundary condition. Considering the theoretical aspects of this intervention, innovative work behavior was conceived based on Social Cognitive Theory: depending on the cognitive abilities of individual employee, the employees' proactive behavior and the psychological environment in which this behavior occurs. The results lent credence to the stability of the suggested model, indicating that the employees who felt more competent in using AI and who were more learning oriented tended to use AI job crafting. AI job crafting, in turn, was positively related to innovative work behavior, suggesting that an employee's proactive attempts to adapt in and reshape their job in relation to AI may be a key behavioral process to innovation. The mediation results also revealed that the path AI self-efficacy to innovative work behavior and learning goal orientation to innovative work behavior were both significant mediation. Confidence in using AI and/or a strong learning orientation, therefore, is not enough for innovative outcomes, workers need to engage with AI in work and working organization as well. It was exacerbated by the factor of psychological safety. The study results support the role modeling of AI by educational leaders for higher positive associations between AI job crafting and innovative work behavior, implying that a secure work environment that allows for interpersonal experimentation and risk taking increases the likelihood of innovative work behavior through AI.

The study adds to the existing literature on AI-related studies through connecting the concepts of AI-specific self-efficacy and learning motivation with a pro-activity behavioral mechanism and the psychological boundary conditions at an individual level. The study integrates these in a single model (Social Cognitive Theory is the holistic perspective underlying the study) in order to provide a more detailed explanation of how employees' personal competencies can be

translated into innovative working behavior with regard to AI. The findings carry profound implications for organizations in Pakistan, as their ability to learn, adapt, experiment and innovate—with evolving technology—becomes critical to successful implementation of AI technologies.

The results suggest that companies that want to foster innovative work behavior in an AI-supported work setting should more strongly focus on fostering employees' AI self-efficacy. Practical AI training is essential in the sense that it is not just raising awareness, it should provide employees with guided activities where they get to practice, and be able to challenge and solve problems. This training should make it understood that AI is not only a technical ability, but one that is integrated into the job/case tasks of the employees. But in parallel, creating a learning culture at work is critical: Workers need to see impactful changes attributable to the introduction of AI as learning opportunities. Enabling scope for ongoing learning and experimentation, knowledge sharing, and skill development of an individual and building learning goals orientation towards proactive behaviors in relation to AI.

Furthermore, organizations need to allow employees space to adapt the way AI can be employed in the creation of their roles by granting them autonomy in certain aspects of their tasks, work flows, processes etc. Organizer should encourage staff to give ideas of where AI can make an impact and enhance current processes, as well as free up routine work, and present opportunities for more creative or innovative work. But this sort of proactive involvement is more effective in producing innovative results when employees feel safe psychologically. Managers, accordingly, need to build workplaces where employees can try and test, ask questions, voice concerns and voice unconventional thinking, without the fear it may bring embarrassment or lead to unfavorable social interaction. It is especially crucial that positive reinforcement is given on correct responses, and for failed experimental attempts.

Additionally, the use of AI is tied to behavioral management, rather than being a technical and/or infrastructure decision. With the introduction of

AI-based systems and processes, look at confidence, learning drive, adapting proactively and psychological safety. Supervisors may help with this by helping to recognize employees' readiness to implement new processes involving the use of AI, and by positively reinforcing employees' first steps and experiments. This kind of supportive managerial behavior can assist in actualizing AI job crafting into employee's observable innovative work behavior and prompt employees to seek out more effective ways to utilize AI in daily work.

Lastly, AI training and development programs should support the wider organizational innovation goals and not just technical skills. How effective AI use can help in the idea generation and ideas being promoted, process improvement and new solutions being implemented should be understood by the employees. The psychological side effects of AI transformation should also be followed: Does AI-related transformation appear to the company to offer a potential for growth or is it perceived as an uncertain and inter-personal risk thereby compromising the employees' acceptance? Psychological safety may or may not influence or be influenced by experimentation with AI, but can enhance the likelihood that innovative work behavior occurs.

REFERENCES

- Bandura, A. (1986). Social foundations of thought and action: A social cognitive theory. Prentice-Hall.
- Bandura, A. (1997). Self-efficacy: The exercise of control. W. H. Freeman.
- Chughtai, A. A., & Arifeen, S. R. (2024). Affective trust in the supervisor and innovative work behavior: The effects of proactive skill development and learning goal orientation. *The Journal of Psychology*, 158(7), 511–532. <https://doi.org/10.1080/00223980.2024.2325664>
- De Jong, J. P. J., & Den Hartog, D. N. (2010). Measuring innovative work behaviour. *Creativity and Innovation Management*, 19(1), 23–36. <https://doi.org/10.1111/j.1467-8691.2010.00547.x>
- Dhir, S., & Vallabh, P. (2025). Do social relationships at work enhance creativity and innovative behavior? Role of psychological safety. *Acta Psychologica*, 253, 104751.
- Dweck, C. S., & Leggett, E. L. (1988). A social-cognitive approach to motivation and personality. *Psychological Review*, 95(2), 256–273. <https://doi.org/10.1037/0033-295X.95.2.256>
- Edmondson, A. (1999). Psychological safety and learning behavior in work teams. *Administrative Science Quarterly*, 44(2), 350–383. <https://doi.org/10.2307/2666999>
- Edmondson, A. C., & Lei, Z. (2014). Psychological safety: The history, renaissance, and future of an interpersonal construct. *Annual Review of Organizational Psychology and Organizational Behavior*, 1, 23–43. <https://doi.org/10.1146/annurev-orgpsych-031413-091305>
- Hair, J. F., Ringle, C. M., Sarstedt, M., & Hult, G. T. M. (2022). A primer on partial least squares structural equation modeling (PLS-SEM) (3rd ed.). SAGE.
- Khan, I., & Usman, M. (2025). Unleashing innovative work behavior in the workplace through leader's cultural intelligence: Mediating role of psychological safety. *Journal of Management Inquiry*, 25(3). <https://doi.org/10.1177/14705958251377283>

- Kock, N., & Hadaya, P. (2018). Minimum sample size estimation in PLS-SEM: The inverse square root and gamma-exponential methods. *Information Systems Journal*, 28(1), 227–261. <https://doi.org/10.1111/isj.12131>
- Li, W., Qin, X., Yam, K. C., Deng, H., Chen, C., Dong, X., Jiang, L., & Tang, W. (2024). Embracing artificial intelligence (AI) with job crafting: Exploring trickle-down effect and employees' outcomes. *Tourism Management*, 104, 104935. <https://doi.org/10.1016/j.tourman.2024.104935>
- Li, X., Gong, Z., Choi, H., & Kang, S.-W. (2026). AI self-efficacy and innovative work behavior in hospitality and tourism: A job demands-resources perspective on work engagement and schedule I-deals. *Behavioral Sciences*, 16(3), 431. <https://doi.org/10.3390/bs16030431>
- Liu, Q., Tian, Q., Li, X., & Tan, H. (2026). How does organizational AI adoption affect employees' job crafting behaviors? An approach-avoidance perspective. *Frontiers in Psychology*, 16, 1690238. <https://doi.org/10.3389/fpsyg.2025.1690238>
- Nazeer, S., & Ahmad, A. (2025). AI anxiety or job crafting? How employees' AI perceptions reshape innovative work behaviour in Pakistan's corporate landscape. *International Journal of Sociology and Social Policy*, 45(11–12), 1187–1204. <https://doi.org/10.1108/IJSSP-04-2025-0227>
- Parker, S. K., & Grote, G. (2020). Automation, algorithms, and beyond: Why work design matters more than ever in a digital world. *Applied Psychology*, 71(4), 1171–1204. <https://doi.org/10.1111/apps.12241>
- Plouffe, R. A., Ein, N., Liu, J. J. W., St. Cyr, K., Baker, C., Nazarov, A., & Don Richardson, J. (2023). Feeling safe at work: Development and validation of the Psychological Safety Inventory. *International Journal of Selection and Assessment*, 31(3), 443–455. <https://doi.org/10.1111/ijsa.12434>
- Pu, T., Lei, R., Siyal, A. W., & Li, Y. (2026). From AI adaptation to innovation: How leader AI crafting shapes employee innovative behavior. *Frontiers in Psychology*, 17, 1847344. <https://doi.org/10.3389/fpsyg.2026.1847344>
- Qiao, Z. (2026). AI-induced job crafting: A systematic review of cognitive appraisal pathways. *Frontiers in Psychology*, 17, 1788385. <https://doi.org/10.3389/fpsyg.2026.1788385>
- Qiu, H., Li, M., Bai, B., Wang, N., & Li, Y. (2022). The impact of AI-enabled service attributes on service hospitableness: The role of employee physical and psychological workload. *International Journal of Contemporary Hospitality Management*, 34(4), 1374–1398. <https://doi.org/10.1108/IJCHM-08-2021-0960>
- Scott, S. G., & Bruce, R. A. (1994). Determinants of innovative behavior: A path model of individual innovation in the workplace. *Academy of Management Journal*, 37(3), 580–607. <https://doi.org/10.2307/256701>
- Tims, M., Bakker, A. B., & Derks, D. (2012). The development and validation of the job crafting scale. *Journal of Vocational Behavior*, 80(1), 173–186. <https://doi.org/10.1016/j.jvb.2011.05.009>

VandeWalle, D. (1997). Development and validation of a work domain goal orientation instrument. *Educational and Psychological Measurement*, 57(6), 995–1015.
<https://doi.org/10.1177/0013164497057006009>

Van Strydonck, I., Decramer, A., & Audenaert, M. (2025). Linking leaders' learning goal orientation to employees' innovative work behaviour, job satisfaction and emotional exhaustion: Leaders' provision of learning-oriented goals and feedback and coaching accuracy. *European Journal of Work and Organizational Psychology*, 34(1), 109–127.
<https://doi.org/10.1080/1359432X.2024.2423433>

Wang, Y.-Y., & Chuang, Y.-W. (2024). Artificial intelligence self-efficacy: Scale development and validation. *Education and Information Technologies*, 29, 4785–4808. <https://doi.org/10.1007/s10639-023-12015-w>

Wrzesniewski, A., & Dutton, J. E. (2001). Crafting a job: Revisioning employees as active crafters of their work. *Academy of Management Review*, 26(2), 179–201.
<https://doi.org/10.5465/amr.2001.4378011>

Yuan, F., & Woodman, R. W. (2010). Innovative behavior in the workplace: The role of performance and image outcome expectations. *Academy of Management Journal*, 53(2), 323–342.
<https://doi.org/10.5465/amj.2010.49388995>

