Computers in Human Behavior 131 (2022) 107215

Contents lists available at ScienceDirect

Computers in Human Behavior

journal homepage: www.elsevier.com/locate/comphumbeh

Impact of artificial intelligence-enabled job characteristics and perceived substitution crisis on innovative work behavior of employees from high-tech firms

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ARTICLE INFO

Keywords:
AI-Enabled jobs
Task characteristics
Knowledge characteristics
Perceived substitution crisis
Innovative work behavior
High-tech firms

ABSTRACT

The importance of artificial intelligence (AI)-enabled systems has been at the forefront of innovation research for the past ten years. The literature has reported the use of AI-enabled systems (AIS) in firms, but there has been a paucity of empirical research on AI-enabled job characteristics of employees of high-tech firms in regard to innovative work behavior (IWB). To address this gap, drawing on job design theory, we proposed a model that describes the roles that AI-enabled task and knowledge characteristics play in employees' IWB. Furthermore, the effects of AIS on human workforce replacement have been a highly debated topic. Drawing on prospect theory, we tested the moderating role of perceived substitution crisis (PSC) triggered by AIS on IWB. We used the partial least square (PLS) technique to test the hypotheses using data from 486 responses collected from an online survey completed by high-tech professionals. The results indicated that AI-enabled task characteristics (job autonomy and skill variety) and knowledge characteristics (job complexity, specialization, and information processing) impact IWB and that AI-enabled job characteristics are strongly associated with IWB under differential effects of PSC. The implications of this study could be used by academicians and practitioners to design AI-enabled job characteristics.

1. Introduction

Artificial intelligence (AI) systems enable employees to sense, reason with, and respond to complex and dynamic business environments (Kaplan & Haenlein, 2019). Over the past decade, AI enabled systems (AIS) have been rapidly transforming organizations by expanding their innovative reach, which has historically been a human task. The implementation of new ideas generated by high-tech employees is required for organizational level innovation that leads to success, competitive advantage, and long-term survival (Lin et al., 2020). Afsar, Badir, & Khan (2015) recommended that stimulating the innovative work behavior (IWB) of employees can be one of the desired ways to foster innovation. It is critical to study the factors that impact the IWB of employees when new AIS are introduced to the workplace, bringing cognitive, emotional, and analytical energies to their roles (Belanche et al., 2019). However, several studies have shown that differences exist in how employees perceive AIS. Ultimately, firms struggle to adapt strategic decision-making processes to successfully reflect the changes from AIS (Dwivedi et al., 2019).

Academicians and practitioners have utilized work design as a central means for organizational success (Schroeder et al., 2021; Waschull et al., 2020). According to Morgeson and Humphrey (2008), work design is the process of structured, organized, enacted, and experienced work and specifically determines the presence or absence of several job characteristics that affect personal and organizational outcomes. The implementation of innovation positively or negatively affects work design (Janssen, 2004), however, several researchers have claimed it is difficult to understand what predicts variations in different work designs (Parker et al., 2017). High-tech firms have been transforming their culture by implementing AIS but, based on one extant body of knowledge, there is scant understanding of how this change affects professional work. To broaden the understanding of how AI capabilities induce change in the work design of employees, we generated the first research question (RQ1): *What are the effects of AIS design on the IWB of high-tech employees?*

According to Kaplan and Haenlein (2020), AI can replace repetitive

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https://doi.org/10.1016/j.chb.2022.107215
Received 12 July 2021; Received in revised form 13 January 2022; Accepted 26 January 2022
Available online 31 January 2022
0747-5632/

and rule-enabled tasks, which leads to the reduction of low-skilled jobs and creation of new higher-skilled jobs. Dwivedi et al. (2019) argued that AIS are likely to displace jobs, including cognitive tasks. It is important for decision makers in high-tech firms to be more strategic in their outlook towards innovation like AI (Featherman & Pavlou, 2003 Employees generally fear new and unknown technology because it brings feelings of uncertainty and is more capable of replacing than assisting them (Dwivedi et al., 2019). Several researchers have focused their studies on understanding whether AI complements or replaces the skills of employees in the labor market. However, none have studied the impact (direct and/or moderating) of employees' perceived substitution crisis (PSC) of IWB, which has led to our second research question (RQ2): *What is the moderating effect of PSC on the relationship between AIS design and the IWB of high-tech employees?*

This paper aimed to explore the effects of AIS design on IWB. We drew our motivation from Hackman and Oldham's job design theory to develop and test the proposed research framework that investigated the influence of task and knowledge characteristics in AI-enabled business environments that promote the creativity of employees in high-tech firms. In addition, we considered the moderating influence of PSC triggered by AIS. The contribution of this study is twofold. First, we expanded on job design theory in the context of how AIS impact job characteristics that propel IWB. Second, we expanded on the knowledge about employees' fear of competition between humans and AIS that may undermine the advantages from and overemphasize the threats of AIS. Departing from existing research (Fan et al., 2018), this paper looked at the moderating influence of PSC on employees' behavior.

The paper is organized as follows: the first section develops the rationale for the proposed research framework and hypotheses, the next section presents the methodology and results, and finally, we present the discussion, implications, conclusion, limitations and future research avenues.

2. Literature review, research framework, and hypotheses

2.1. AI-enabled systems and innovation

AIS are expected to create approximately 50 million jobs worldwide by 2022 (Kaplan & Haenlein, 2020). The era of AIS has progressed to levels where chatbots, voice assistance, autonomous planning and scheduling, robots, and autonomous vehicles can be used via machine intelligence. These computer applications can sense, reason with, and respond to the environment (Duan et al., 2019) and have become an integral part of digital strategies with natural language processing, machine learning, big data, and intelligent predictive analytics. Research suggests that a well-crafted HR practice using AI can deliver better employee outcome and HR performance (Rehman et al., 2020a; Rehman et al., 2020b). AI-mediated social exchange between employees and bots has resulted in higher level satisfaction and retention. Furthermore, AI has redefined the organization's perspective towards innovation. AI facilitates information processing at a larger level to generate new ideas and avenues which would not be possible if human processing takes place (Rehman et al., 2020a; Rehman et al., 2020b). The implementation of innovation through AIS requires firms to alter their business environments and information ecosystems (Dwivedi et al., 2019). AIS significantly increases employee efficiency by monitoring and controlling processes in real-time to respond to changing uncertain environments and can lead to entirely new forms of interaction between employees and machines (Kaplan & Haenlein, 2020). This advancement not only changes organizational culture, but significantly affects work design. AIS may create or redesign work that requires empathy, creativity, and cognition from employees to be innovative. The increasing complexity of AIS could reduce IWB, making it impossible to clearly account for specific AI-driven outcomes (Belanche et al., 2019). Therefore, changes to the IWB caused by AIS are not solely determined by the AI itself, but also by the choices made by firms to organize work around the AIS.

2.2. The influence of AI-enabled job characteristics on IWB

According to Janssen (2004), IWB is the intentional creation, promotion, and application of novel ideas within a job role, work group, or organization to improve organizational performance. This definition is closely related to employee creativity and demonstrates that IWB helps to drive effective processes, products, and procedures (Saether, 2019). When an employee produces innovative ideas about processes, products, or procedures, the support provided by the work role, group, or organization to implement the ideas is a crucial step for completing the innovation process (Kör et al., 2020). Several researchers (Saether, 2019; Shanker et al., 2017) have studied IWB to better understand innovative improvements in organizations. IWB includes thinking about the unfulfilled needs of stakeholders, problems in existing work methods, or novel solutions to address problems that arise from changing trends (Afsar et al., 2014). Several high-tech organizations strive to enhance their employees' IWB to survive and gain competitive advantage in the turbulent global business environment, and firms that focus on prolifically innovative employees are showing signs of success (Shanker et al., 2017). According to the theory of resource and capabilities, high-tech organizations need technological capabilities, like AI, to foster IWB that will be challenging for competitors to mimic (Miao, 2020). In addition, job design of employees of high-tech firms has been considered an important situational contributor to IWB (Waschull et al., 2020). Currently, AIS is not mandated by organizational policies, thus, any behavior towards AIS is IWB (Dwivedi et al., 2019). According to Liang et al. (2015), employees will not exhibit IWB unless they are sufficiently motivated. To understand the impact of AI on IWB, we propose that the AI-enabled job characteristics that play a critical role in developing positive IWB be analyzed (Fig. 1).

In existing innovation research, links between various technological job characteristics (e.g., gig work, complex systems) and IWB have become a research hotspot for academicians and practitioners. However, according to Dwivedi et al. (2019), there is a dearth of empirical research analyzing AI job design attributes that trigger IWB in the employees of high-tech firms. AI-enabled jobs comprise of some characteristics that have a psychological bearing on an employee's intention to innovate. Fan et al. (2018) argued that the variations in IWB in high-tech organizations could be explained by how employees perceive certain characteristics of the AI-enabled jobs.

Based on job design theory offered by Humphrey et al. (2007) and Martinez (2017), we focused our research on task and knowledge characteristics by acknowledging that AI-enabled jobs can be designed/redesigned to heighten task and/or knowledge characteristics to enhance the innovative behavior in high-tech firms' employees. Similar to the Martinez (2017) study, we focused on investigating the impact of two AI-enabled task dimensions (job autonomy and skill variety) and three AI-enabled knowledge dimensions (job complexity, specialization, and information processing) to predict employees' IWB (Fig. 1). We selected these job characteristics as they connect with previous changes in work design originating from digital technologies (Schroeder et al., 2021). We did not examine social characteristics, like feedback, communication outside the organization, and social support or work characteristics, like ergonomics and physical demands, due to a lack of theoretical base connecting AI-enabled jobs to these variables and to their general dearth of empirical study in emerging technology, like big data and virtual reality (Dwivedi et al., 2019; Verma, 2018).

2.3. AI-enabled task dimensions

Job autonomy (JA) refers to the extent to which employees determine the pace, methods, and sequence while accomplishing tasks (Hackman & Oldham, 1980). JA gives employees freedom to optimize work, decide on procedures to follow, and select equipment to use

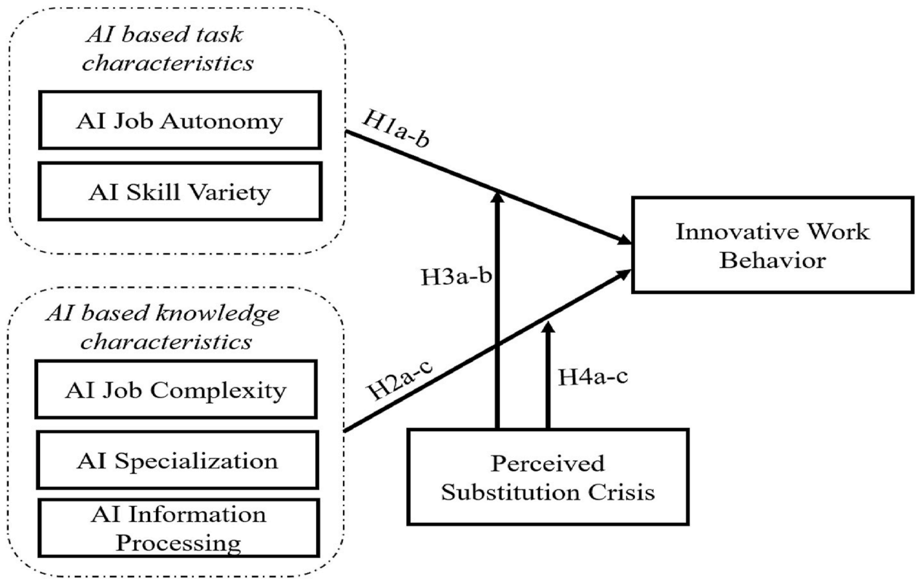

Fig. 1. Proposed research model.

(Carlson et al., 2017). AI-JA allows employees to leave routine, intuitive, and uncertain tasks behind and try more analytical and fact-enabled solutions (Jarrahi, 2018). An employee with greater AI-JA can generate fresh ideas through AI systems resulting in higher probability of IWB. It is likely that employees with higher levels of control (conscious data-driven reasoning and logical deliberation) over tasks due to AIS will exhibit more IWB in the form of idea generation and application. Therefore, the hypothesis for ***Proposition H1a*** is: *AI-enabled job autonomy has a positive impact on the IWB of high-tech workers.*

Skill variety (SV) is defined as the degree to which an employee uses various personal and professional skills to perform work (Hackman & Oldham, 1980). The level of AI-SV describes how different technical and analytical skills are needed to perform AI-enabled jobs to foster new idea creation (Bayo-Moriones et al., 2010). According to Martinez (2017), certain skills (e.g., critical thinking, creativity, collaboration, and communication) and analytical capabilities are required to perform AI-enabled jobs. Employees in high-tech firms with multiple technological skills have been found to demonstrate more IWB than those without the same skills (Bayo-Moriones et al., 2010). If AI-enabled jobs require high-tech professionals to perform different tasks, professionals might feel more intellectually challenged when applying their technical and analytical skills to develop novel solutions. High-tech professionals might also exhibit more IWB on a diverse range of topics while using AI-enabled skills. Therefore, the hypothesis for ***Proposition H1b*** is: *AI-enabled skill variety has a positive impact on the IWB of high-tech workers.*

2.4. AI-enabled knowledge dimensions

Job complexity (JC) is the perceived difficulty and load to perform a given task (Hackman & Oldham, 1980). AI-enabled jobs may be highly uncertain and difficult due to unclear understandings about the availability and use-cases of AIS. AI-enabled tasks could be more complex and completing them could satisfy the professionals' needs to feel competent (Fan et al., 2018). Thus, high-tech professionals need to maximize their knowledge and abilities with constant acquisition of AIS and advanced analytical methods (Bayo-Moriones et al., 2010). Several innovation researchers found AI-JC to be a driver for employees' synthesis of technological knowledge to innovate (Carlson et al., 2017; Martinez, 2017). Thus, high levels of AI-JC in high-tech professionals stimulate IWB, engage higher cognitive demands to generate unique solutions, and demonstrate more workplace enthusiasm than employees with monotonous tasks. Therefore, the hypothesis for ***Proposition H2a*** is: *AI-enabled job complexity has a positive impact on the IWB of high-tech workers.*

Specialization (Sp) refers to performing specialized tasks, using specialized skills, or processing specialized knowledge for a job (Hackman & Oldham, 1980). AI-Sp should support AI applications, algorithms, and analytical approaches, like the methodical information gathering for reasoning and logical deliberation for high-tech workers, since it allows them more time to focus on developing innovative solutions from their expertise (Dwivedi et al., 2019). AI-Sp reflects a depth of technological knowledge and analytical skill in high-tech professionals that are more likely to lead to innovative behavior than for workers with mundane tasks. Therefore, the hypothesis for ***Proposition H2b*** is: *AI specialization has a positive impact on the IWB of high-tech workers.*

Information processing (IP) is the degree to which a job requires an employee to focus, manage, and process data and information for problem solving (Hackman & Oldham, 1980). According to Dwivedi et al. (2019), AI-enabled jobs transform IP and cognitive decision making. Several researchers have suggested that levels of monitoring, processing, mechanization, and automation of information in AI-enabled jobs differ from other jobs (Belanche et al., 2019). AI-IP reduces uncertainty, complexity, and equivocality due to intuitive decision making. However, this extensive analytical decision requires methodical information searching, gathering, and analyzing from high-tech professionals. This higher level of IP in AI-enabled jobs changes how high-tech employees approach their tasks and may lead to IWB while completing them. Therefore, the hypothesis for ***Proposition H2c*** is: *AI-IP has a positive impact on the IWB of high-tech workers.*

2.5. Potential moderating role of PSC triggered by AI-enabled systems

According to prospect theory (Kahneman & Tversky, 1979), fear is a stronger driver for human choice than pleasure. PSC is the fear that employees have of being replaced by AIS and this fear can affect their IWB (Featherman & Pavlou, 2003he PSC triggered by AIS as a new construct motivated by the artificial-intelligence medical diagnosis support system from Featherman and Pavlou (2003). With the rapid development of AI-enabled applications in different business processes, like supply chain, marketing, procurement, human resource management, and research & development, some professionals with routine jobs are concerned that their skills and authority will be challenged by AIS. AI-enabled jobs might offer more efficient service and lower working hours, and employees' fears of replacement can underestimate the gains and overestimate the threats of AIS. However, according to Kaplan and Haenlein (2020), even with astonishing technological developments in business over the last 40 years, the need for skilled labor has not diminished, and we anticipate that PSC triggered by AIS will be a positive moderator. Employees who are afraid of AIS can make more evidence-based decisions to think radically out of the box and improve their innovation. By being more mentally demanding, PSC could intensify the focus that high-tech employees project toward redesigning task characteristics (JA without the opportunity to monitor employees and SV) and knowledge characteristics (JC, Sp, and IP) (Martinez, 2017). If high-tech employees find their AI-enabled jobs have a significant impact on physical and cognitive tasks and, at the same time, perceive a high appreciation of AI-enabled innovation in the firm, their IWB will increase. Therefore, the hypothesis for ***Proposition H3*** is: *Higher PSC levels will create stronger relationships between task characteristics (H3a: AI-JA, H3b: AI-SV) and IWB, and vice versa.* Additionally, the hypothesis for ***Proposition H4*** is: *Higher PSC levels will create stronger relationships between knowledge characteristics (H4a: AI-JC, H4b: AI-Sp, H4c: AI-IP) and IWB, and vice versa.*

3. Methodology

3.1. Sampling and data collection

According to Qaiyum and Wang (2018), India's growth is propelled by the innovation and business sophistication of its high-tech sector. Most Indian high-tech firms have attached great importance to the application of AIS for innovation and have increasingly used AIS, like chatbots, digital assistance, robots, and voice-assisted service, to support their businesses and provide innovative products or services (Dwivedi et al., 2019). To understand how AIS affect the IWB of employees, the participants were selected from firms in the high-tech sector (as classified by OECD, 2009) and listed in the database of the Indian Chamber of Commerce & Industry. We conducted an online survey to collect detailed data on AI-enabled job characteristics, IWB, and demographics. We utilized a simple random sampling technique and obtained 486 complete and useable responses. The respondents were employees who worked with some AI tools. Along with the survey questionnaire, we emailed the research objectives, the significance of the study, and respondent confidentiality. The respondents and their firms' compositions are summarized in Table 1.

Table 1
The sample profile ($n = 486$).

Respondents Composition	Count	Firm Composition	Count
Gender		Industry	
Female	146	Information Technology	144
Male	340	Manufacturing	123
Respondent's age		Medical & Healthcare	78
20–30	43	Transportation, Logistics & Courier	10
31–40	105	Chemical & Pharmaceuticals	94
41–50	165	others	37
51–60	173	No. Of Employees	
Education		≤250	129
High School	12	251–800	85
Graduation	216	>800	272
Post-graduation	238	Turnover (in INR millions)	
Others	20	Turnover ≤750	96
Role in organization		750 < Turnover ≤3000	152
CEO/COO/CIO/CFO	65	Turnover >3000	238
V.P., General Manager, etc.	127		
Director, Controller, etc.	69		
Manager, Senior Analyst, etc.	225		

3.2. Measurement and instrument development

The survey was developed in three steps. First, items that could measure the constructs were identified from existing studies and adapted for AIS. Second, the questionnaire was pre-tested to ensure the face validity of the instrument. Third, respondents were asked to rate five AI job characteristics, PSC, and IWB on a five-point Likert scale. The five job characteristics were measured with items/scales adapted from previous general management studies and reworded to be relevant to AI-enabled jobs. AI-JA was captured with four items adapted from the technology-enabled job autonomy scale from Carlson et al. (2017). AI-SV and AI-JC were measured with three items for each adapted from Bayo-Moriones et al. (2010). AI-Sp (three items) and AI-IP (two items) were adapted from Waschull et al. (2020). PSC (three items) was a new measure motivated by Fan et al. (2018) and IWB was adapted from Kör, Wakkee, & van der Sijde (2021).

3.3. Data analysis

With SmartPLS 3.2.7, we analyzed the measurement and structural models using the partial least square-structural equation modelling (PLS-SEM) technique, which is used for complex models, such as those with large numbers of constructs or complex relationships, like moderation (Hair et al., 2014).

3.4. Measurement model

Since we used a cross-sectional survey design for data collection, there was potential for common method bias (CMB) (Hair et al., 2017). As suggested by Hair et al. (2014), the effect of CMB was reduced by developing clear and concise statements, avoiding complicated and double-barreled questions, defining unfamiliar and ambiguous terms, and labeling all scale points. Furthermore, we tested CMB using Harman's one factor test. The Harman's test showed that the single factor explained 43.28% of the total variance. Thus, CMB was not a major issue for the data collection in this study.

Before conducting factor analysis, we ensured the quality of the measurement items' data with the normality test. Appendix summarizes the mean, standard deviation, skewness, and kurtosis of all items. All items' kurtosis and skewness values were less than the threshold value of two and revealed no normality issues in the dataset. We examined Cronbach's alpha (CA) and composite reliability (CR) values to test reliability. Hair et al. (2017) recommended minimum CA and CR values of 0.6 and 0.7, respectively. In this study, minimum CA and CR values were above 0.669 and 0.857, respectively (Table 2), thus showing no reliability issues. We used the average variance extracted (AVE) value to examine the convergent validity of constructs. The minimum threshold value of AVE is 0.5 (Hair et al., 2017). In this study, the minimum AVE value was 0.658, thus showing that constructs in this study explained a minimum 65.8% variance (Table 2). As illustrated in Table 3, we tested the discriminant validity of constructs using the Fornell-Larker criterion and the Heterotrait-monotrait (HTMT) ratios. In the Fornell-Larker criterion, the square root of the AVE of each construct should exceed the correlation values. Hair et al. (2014) recommended that the HTMT value should be smaller than one to distinguish between two factors and in this study HTMT ratios were <1 (Table 3). Thus, the Fornell-Larker criterion and HTMT values signified that each construct was unique and explicitly independent.

3.5. Structural model

This section examined the structural relationships between variables and model fit. Table 4 summarizes the results of bootstrapping analysis based on 1000 sub-samples. In task characteristics, we found a significant positive relationship between AI-JA and IWB (H1a: $\beta = 0.085$, $p < 0.1$). However, we found a significant but reversed (negative) impact of

Table 2
Constructs, items, and reliability.

Constructs	Items	Statements	Item loading	AVE	CR	CA
AI-JA (Carlson et al., 2017)	AI-JA1	AIS help to make decisions in real-time.	0.785	0.658	0.885	0.826
	AI-JA2	AIS help to make decisions about what methods I should use to complete my work.	0.850			
	AI-JA3	AIS help to perform a variety of tasks in a short time.	0.779			
	AI-JA4	AIS help to get direct and clear information about the effectiveness (i.e., quality and quantity) of my job performance.	0.828			
AI-SV (Bayo-Moriones et al., 2010)	AI-SV1	Jobs using AIS require tracking of more than one thing at a time.	0.928	0.863	0.927	0.842
	AI-SV2	Jobs using AIS require a variety of skills to complete the work.	0.931			
AI-JC (Bayo-Moriones et al., 2010)	AI-JC1	Using AIS, I can do multiple tasks/activities at a time.	0.782	0.686	0.867	0.771
	AI-JC2	Using AIS, my job becomes comparatively simple.	0.857			
	AI-JC3	Using AIS, my job becomes comparatively uncomplicated.	0.843			
AI-Sp (Waschull et al., 2020)	AI-Sp1	Jobs using AIS require high specialization of purpose, tasks, or activities.	0.921	0.837	0.939	0.904
	AI-Sp2	Jobs using AIS require highly specialized knowledge and skills.	0.911			
	AI-Sp3	Jobs using AIS require in-depth advanced technological expertise.	0.912			
AI-IP (Waschull et al., 2020)	AI-IP1	Jobs using AIS require a lot of information analysis.	0.842	0.750	0.857	0.669
	AI-IP2	Jobs using AIS require to engage in a less amount of thinking.	0.890			
PSC (Fan et al., 2018)	PSC1	I think that AIS will replace employees in the future.	0.802	0.724	0.913	0.873
	PSC2	I think using AIS for a long time will make managers dependent on them.	0.847			
	PSC3	I think the rise and development of AIS will likely lead to unemployment.	0.875			
IWB (Kör et al., 2020)	IWB1	I create new ideas for improvement.	0.914	0.869	0.952	0.925
	IWB2	I often search out new working methods, techniques, or instruments.	0.941			
	IWB3	My ideas generate original solutions to problems.	0.950			

Note: Appendix contains detail list of acronyms.

Table 3
Fornell-Larker criterion and the Heterotrait-monotrait (HTMT) ratios.

	Fornell-Larker criterion						
	AI-IP	AI-JA	AI-JC	AI-SV	AI-Sp	IWB	PSC
AI-IP	0.866						
AI-JA	0.423	0.811					
AI-JC	0.400	0.611	0.828				
AI-SV	0.649	0.493	0.435	0.929			
AI-Sp	0.636	0.501	0.406	0.700	0.915		
IWB	0.422	0.453	0.442	0.365	0.409	0.932	
PSC	0.456	0.486	0.438	0.482	0.468	0.650	0.851
	Heterotrait-monotrait (HTMT) ratios						
	AI-IP	AI-JA	AI-JC	AI-SV	AI-Sp	IWB	PSC
AI-IP							
AI-JA	0.564						
AI-JC	0.552	0.766					
AI-SV	0.709	0.588	0.542				
AI-Sp	0.612	0.578	0.482	0.812			
IWB	0.534	0.518	0.522	0.413	0.441		
PSC	0.593	0.566	0.532	0.566	0.521	0.717	

Table 4
Structural model and model fit.

Model *Dependent variable: IWB*	Model 1 *(Baseline Model)*	Model 2 *(Job Characteristics Model)*	Model 3 *(Moderation Model)*
Independent variables:			
AI-JA		0.193 (3.720) ***	0.085 (1.770) *
AI-SV		−0.080 (1.137) n.s.	−0.156 (2.330) **
AI-JC		0.194 (3.448) ***	0.128 (2.382) **
AI-Sp		0.150 (2.099) **	0.111 (1.757) *
AI-IP		0.218 (3.952) ***	0.133 (2.496) **
PSC			0.509 (10.146) ***
Interaction terms:			
PSC * AI-JA			0.105 (2.864) ***
PSC * AI-SV			0.110 (3.209) ***
PSC * AI-JC			0.095 (2.879) ***
PSC * AI-Sp			0.085 (2.658) ***
PSC * AI-IP			0.053 (1.677) *
Control Variables			
Gender	0.065 (1.238) n.s.	0.087 (0.861) n.s.	−0.028 (0.791) n.s.
Age	0.105 (1.846)*	0.106 (1.562) n.s.	0.035 (0.984) n.s.
Education	−0.072 (1.534) n.s.	−0.021 (0.124) n.s.	0.012 (0.358) n.s.
Role in Organization	0.078 (1.320) n.s.	0.074 (0.080) n.s.	0.008 (0.229) n.s.
R^2	0.018	0.311	0.490
Adjusted R^2	0.010	0.298	0.478
SRMR	0.025	0.046	0.047
Q^2	0.012	0.260	0.410

AI-SV on IWB (H1b: $\beta = -0.156$, $p < 0.05$). In knowledge characteristics, as predicted, AI-JC (H2a: $\beta = 0.128$, $p < 0.05$), AI-Sp (H2b: $\beta = 0.111$, $p < 0.1$), and AI-IP (H2c: $\beta = 0.133$, $p < 0.01$) were positively associated to IWB; thus, hypotheses 2a, 2 b, and 2c were supported.

We used the moderation analysis guideline proposed by Hair et al. (2017) to test the moderating effect of PSC on job characteristics and IWB. Table 4 show that the relationship between IWB and the two task characteristics were positively moderated by PSC (PSC*AI-JA → IWB [H3a: $\beta = 0.105$, $p < 0.01$]; PSC*AI-SV → IWB [H3b: $\beta = 0.110$, $p < 0.01$]). The relationship between IWB and all three knowledge characteristics were positively moderated by PSC (PSC*AI-JC → IWB [H4a: $\beta = 0.095$, $p < 0.01$]; PSC*AI-Sp → IWB [H4b: $\beta = 0.085$, $p < 0.01$];

PSC*AI-IP → IWB [H4c: β = 0.053, p < 0.1]). These findings support hypotheses H3a, H3b, H4a, H4b, and H4c and the results confirm that PSC had a positive effect on task and knowledge characteristics of AI-enabled jobs. We examined the effect size of the moderator using Cohen's (1988) f^2 formula. According to Hair et al. (2014), the average effect size of moderation is 0.9%, 2.1%, 2.3%, 1.7%, 1.5%, and 1.6% for the PSC moderation between AI-JA, AI-SV, AI-JC, AI-Sp, and AI-IP. In this study, IWP showed at least a medium moderating effect on PSC.

3.6. Model fit

We calculated and compared model 1 (baseline), model 2 (job characteristics), and model 3 (moderation) using R^2, Q^2, and standardized root mean square residual (SRMR) values (Table 4). The explanatory power of each model was measured by R^2. The threshold values for R^2 were >0.67 (high predictive accuracy), >0.33 (moderate effect), >0.19 (low effect), and <0.19 (unacceptable). The average R^2 of baseline, job characteristics, and moderation models were 0.018 (low), 0.311 (low), and 0.490 (moderate), respectively. The moderation model had more explanatory power than the job characteristics model because the former had more predictors than the latter. Next, we tested the model fit with an SRMR value; an SRMR value of 0.8 or below indicated adequate fit and all three models (Table 4) met this criteria. We used Stone-Geisser's Q^2 to predict the models' capability to predict. Q^2 values were low for model 1 (0.012), medium for model 2 (0.260), and high for model 3 (0.410), indicating high predictive relevance of the moderation model.

3.7. Importance-performance map analysis (IPMA)

The current study adopted importance-performance map analysis (IMPA) to present the findings from the managerial perspective. IMPA is used to indicate the strength of enabling variables. Fig. 2 shows that variables related to AI based task characteristics, AI-JA is most important variable while AI-SV is the least important for IWB. A one-point increase of AI-JA performance will lead to an increase in the performance of IWB by a value of 0.252, while a one-point decrease of AI-SV performance will lead to increase in the performance of IWB with the value of 0.093. Further, variables related to AI based knowledge characteristics, AI-JC (0.226) is more important as compared to the other two AI based knowledge characteristics (AI-IP: 0.200; AI-SP: 0.155) for achieving a higher level of IWB performance.

4. Discussion

The purpose of this study was to examine how five AI-enabled job characteristics influenced the IWB of employees at high-tech firms. Drawing motivation from job design theory, we found that both AI-enabled task and knowledge characteristics had a significant impact on IWB.

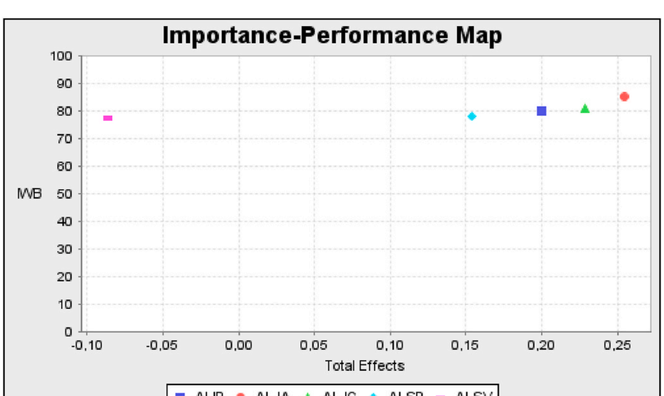

Fig. 2. Importance-Performance Map (IPMA) by constructs.

4.1. The influence of task characteristics on IWB

This study showed that AI-JA positively affected IWB (Hypothesis H1a). In future, employees will either guide or be guided by AIS to generate new ideas from crucial and tailored information. This coincides with the study by Bysted (2013) and Duan et al. (2019). AIS may lead to a significant reduction of mundane jobs and could help high-tech professionals focus more on innovation.

AI-SV was significantly, but negatively, associated with IWB (Hypothesis H1b). Thus, employees' innovative behavior will decrease if they feel that AI-enabled jobs require a more diverse skill set. This finding aligned with the study by Martinez (2017). AI-enabled jobs require employees to be equipped with technical, cognitive, and social skills to handle automation and process a range of information for planning, problem solving, and complex decision making. The dynamic and self-learning nature of AIS requires employees to engage in lifelong learning to meet the changing skill requirements of future AI-enabled jobs (Fan et al., 2018). The efforts (like problem solving skills and understanding complex AIS) to enrich jobs by increasing AI-SV could cause additional problems instead of providing solutions (Dwivedi et al., 2019).

4.2. The influence of knowledge characteristics on IWB

This study showed that AI-JC positively affected IWB (Hypothesis H2a). AI-enabled jobs make substantial emotional, intellectual, and cognitive demands on high-tech employees (Kaplan & Haenlein, 2020). In addition, AI-enabled jobs require creativity, judgement, and empathy from employees, which is consistent with several research perspectives (Liang et al., 2015). AI-JC was intertwined with innovative behavior to some degree, as the complexity of an AI-enabled job could involve tasks that are strategic and less repetitive.

According to Lin et al. (2020), high-tech firms are facing fast advancements in AIS that make AI-enabled jobs much more specialized and that leverage specialist knowledge and expertise, especially upskilling. Thus, AI-Sp plays an important role in developing employees' IWB (Hypothesis H2b). The AIS led to data-driven decision making, creating the need for technical and analytical capabilities. AI-Sp not only avoids errors, but also creates conditions for innovative behavior.

AI-IP most strongly impacted IWB, underlying the particular characteristics of AI-enabled jobs in terms of using automation for decision making and innovation (Hypothesis H2c). AI-enabled jobs included more computational procedures and analytical activities that high-tech employees needed to be aware of. Furthermore, AI-enabled tasks were more unstructured and challenging and required greater coordination of resources like planning, maintenance, quality management, and empathetic behavior (Liang et al., 2015). According to Duan et al. (2019), AIS will induce a gradual shift towards more information processing and complex tasks, while supporting employees' actions related to innovation.

4.3. The moderating role of PSC on IWB

Based on prospect theory, it is expected that uncertain factors, like the fear of being replaced by AI, impact high-tech professionals in being innovative, both directly and by moderating the effect of PSC. Employees with high levels of PSC know their AI-enabled jobs will lead to innovative initiatives, and previous studies found that PSC insignificantly influenced employees' behavior (Fan et al., 2018). This study demonstrated that the fear of being replaced by AIS made employees more innovative when they were given autonomous work tasks, training to deploy AI skills, freedom to coordinate and control complex AI tasks, training in AI specialization, and freedom to augment IP functions.

Employees with high levels of PSC converted AI-enabled job characteristics into IWB more effectively than employees with low levels of PSC. Thus, high-tech firms should consider the degree of employees' PSC as a boost to impact AI-enabled job characteristics.

5. Implications

5.1. Managerial implications

Due to current advancements in technology (e.g., big data, machine learning, computation, internet of things), AIS are believed to improve employees' decision-making abilities, boost their analytical skills, and heighten creativity to be more responsive to innovative demands. Strategies for carefully evaluating, designing, and/or redesigning AI-enabled jobs to motivate high-tech employees to appreciate their jobs have been recommended to improve employees' IWB (Verma et al., 2020).

In the context of job design theory, task and knowledge characteristics are factors associated with IWB. Innovation managers and human resource managers should come together to give high-tech employees with more space and a powerful sense of control (like transparency and accountability) to empower their employees to demonstrate innovative behavior while using AIS. Orientation sessions that establish well-defined perceptions of the relevance of AI-enabled jobs will help high-tech employees understand the responsibilities and liabilities of these jobs.

In the context of AI, SV is a double-edged sword and measures to increase AI-SV may not always be appropriate or beneficial. Managers must carefully design strategies while gauging their employees' tolerance of increased AI and other technical skills requirements. Furthermore, additional support resources (like training or mentorship) should be made accessible at the right time. High-tech employees show more positive behavior when they have close knit social support at the time of learning and using novel AI skills. Aligned with prospect theory, it can be hard for management of high-tech firms to increase the PSC levels of employees and mitigate the fear they have of AI-enabled jobs. Thus, top management of high-tech firms can focus on communicating how AI-enabled tasks contribute to organizational objectives and ultimately create organizational value. The results of this study could contribute to the recruitment process of high-tech employees, where the importance of PSC triggered by AIS can be used to get an idea of potential employees' innovative skills.

Based on IMPA results (Fig. 2), AI-JA is the most important factor among AI based task and knowledge characteristics that influences IWB. Therefore, the IPMA results suggest that to achieve a higher level of AI-JA, high-tech firms are suggested to have clear information and communication about benefits from AIS including real-time decision making, performing a variety of tasks in a short time, direct and clear information of AIS impact on the job performance etc. among professionals.

5.2. Theoretical implications

In this study, job design theory examined the influence of AI-enabled task and knowledge characteristics and prospect theory was used to model PSC triggered by AIS as a moderator. This study has contributed to the field of innovation management by extending AI research into human resource management research. This study extended the current understanding in the AI literature by including the behavioral economics of employees rather than only the technical aspects of AI. This study also contributed to organizational behavior research by incorporating AI-enabled job design as an antecedent to employees' IWB. Furthermore, in response to the call of Lee and Lee (2018) to retire job design theory, our study demonstrated that it may not necessarily be prudent to do so, but more worthy to modify job design theory by looking into potential moderators and mediators relevant to a particular context, since PSC (derived from prospect theory) triggered by AIS showed a significant moderation effect.

6. Limitations and future research

The dataset included a wide range of high-tech firms representing a variety of industries, and readers should evaluate the findings and generalization of the results with caution. In future, researchers should scrutinize the findings of this study in other contexts, like a specific high-tech industry (e.g., IT, manufacturing) or country, to ensure higher variance levels in the dataset. Another limitation is that we only examined the impact of job characteristics on IWB and future researchers would benefit by studying other organizational factors, like leadership, innovation climate, or organizational support. Researchers should also determine whether the moderating role of PSC extends to other characteristics, like social or work characteristics. We used a cross-sectional research design to test the proposed research framework and future researchers would benefit by conducting a longitudinal study, mixed-method, or multi-level research design to understand the impact of AI-enabled job characteristics. In addition, we used a structured survey to reflect the employees' perceptions and behaviors. Thus, future research should consider interviews and focus group studies to get meaningful insights into AI-enabled job designs.

7. Conclusion

By grounding this study with job design theory and prospect theory, we sought to examine theoretically sound and practically feasible AI job characteristics to measure their impact on innovative behavior. The key findings were that the task and knowledge characteristics of AI-enabled jobs are vitally important for inducing IWB among employees of high-tech firms. Furthermore, this study addressed an important gap in the literature by addressing how PSC explains the differential effects of AI-enabled job characteristics on IWB. Overall, this study was important and unique because it integrated diverse fields, like innovation management, social science, and human resource management, to conduct AI-based research.

Author contribution form

Surabhi Verma: Conceptualization, Methodology/Study design, Formal analysis, Writing – original draft, Writing – review and editing, Project administration **Vibhav Singh**: Conceptualization, Methodology/Study design, Data curation, Writing – review and editing, Project administration.

No conflict of interest exists.

We wish to confirm that there are no known conflicts of interest associated with this publication.

Source of funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors."

Appendix

Table 5
List of Acronyms

Acronyms	Details
AI	Artificial Intelligence
AIS	AI enabled systems
AI-JA	AI enabled Job Autonomy
AI-SV	AI enabled Skill Variety
AI-JC	AI enabled Job Complexity
AI-Sp	AI enabled Specialization
AI-IP	AI enabled Information Processing
PSC	Perceived Substitution Crisis
IWB	Innovative Work Behavior

Table 6
Summary if mean, standard deviation, skewness, and kurtosis of items

Constructs	Items	Mean	SD	Kurtosis	Skewness
AI enabled Job Autonomy	AI-JA1	4.506	0.657	1.980	−1.292
	AI-JA2	4.362	0.688	1.200	−0.957
	AI-JA3	4.502	0.647	0.925	−1.127
	AI-JA4	4.403	0.744	1.905	−1.320
AI skill variety	AI-SV1	4.272	0.773	0.246	−0.860
	AI-SV2	4.183	0.849	0.695	−0.985
AI enabled job complexity	AI-JC1	4.519	0.637	0.795	−1.123
	AI-JC2	4.280	0.811	0.374	−0.948
	AI-JC3	4.074	0.890	0.445	−0.830
AI-specialization	AI-Sp1	4.198	0.813	0.204	−0.838
	AI-Sp2	4.216	0.844	0.936	−1.044
	AI-Sp3	4.257	0.815	0.849	−1.054
AI information processing	AI-IP1	4.364	0.784	2.643	−1.409
	AI-IP2	3.922	1.027	−0.091	−0.779
Perceived substitution crisis	PSC1	4.333	0.714	0.409	−0.861
	PSC2	4.103	0.850	−0.379	−0.622
	PSC3	4.356	0.714	1.708	−1.086
Innovative work behavior	IWB1	4.249	0.710	1.001	−0.816
	IWB2	4.210	0.773	0.485	−0.810
	IWB3	4.222	0.775	1.040	−0.940

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