



**The Impact of Employee Usage of Generative AI on Innovative Work Behavior and the
Mediating Role of Self-Efficacy**

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Project Period: October 2023 – June 2024
Project Theme: Employee Usage of Generative AI
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Abstract

As more employees use generative AI for work, it becomes increasingly interesting to investigate the potential outcomes of AI use. This study thus aimed to investigate the relationship between the use of generative AI and innovative work behavior (IWB), with a particular focus on self-efficacy as a mediating factor. The sample of the study consisted of 140 employees who used generative AI for work activities on a regular basis. To answer the research question, a quantitative cross-sectional study at the individual level was carried out. IBM SPSS Statistics 28 was used to conduct regression and reliability analyses, as well as an exploratory factor analysis, to evaluate model fit and check for violations of assumptions. Hayes's Process Model 4 was used in order to test the hypothesized model. The findings of the current study show that there is a positive relationship between generative AI usage and IWB and self-efficacy and IWB. Results of the analysis of the relation between AI usage and self-efficacy and the mediating effect of self-efficacy were non-significant. The present study contributes to our understanding of how using generative AI can impact employee behavior, with the findings suggesting that using generative AI tools allows employees to engage in more innovative behaviors. Organizations can improve the innovative behavior of their employees and maintain a competitive advantage in an ever-changing business landscape by encouraging the use of generative AI. Limitations, implications for practice and theory, and recommendations for future research are discussed.

Keywords: generative AI, innovative work behavior, self-efficacy, innovation

Introduction

Due to the significant impact artificial intelligence (AI) has on everyday life, businesses, and work, AI has become one of the most discussed topics of the 21st century (Budhwar et al., 2023). The world is undergoing a transformation fueled by machine learning and AI, dubbed the fourth industrial revolution by some (Syam & Sharma, 2018). Noy and Zhang (2023) argue that many of the recent advances in generative AI have widespread implications for the labor market, and the challenge for organizations in these times lies in their ability to innovate in the face of a highly dynamic environment (Wijayati et al., 2022). Literature shows that AI could either replace people in some occupations or complement human workers to boost productivity in others (Noy & Zhang, 2023). Generative AI technologies emulate human cognitive and behavioral processes within machines and can help in many fields; they can help with visual recognition, decision-making, and employee learning (Berşe et al., 2023). ChatGPT, a generative AI example, has quickly become one of the most popular chatbots for text generation (Xue et al., 2023). It has become an invaluable tool for many industries due to its capacity to understand context and generate responses that are human-like (Meşe et al., 2023). With generative AI's growing popularity, it is crucial to comprehend how its use affects employee performance and behavior.

Businesses will need to rely more on generative AI to enhance employee and organizational performance in order to boost innovation and productivity (Crews, 2019). The analysis by Wamba-Taguimdje et al. (2020) highlights the potential of generative AI to increase performance and innovation. Furthermore, there is evidence to suggest that using generative AI chatbots like ChatGPT may, amongst others, lead to greater efficiency (Meşe et al., 2023); simplify complex and challenging tasks (Agathokleous et al., 2023); enhance knowledge and skills (Berşe et al., 2023); and increase work engagement and employee performance (Wijayati et al., 2022). Therefore, rather than completely replacing humans, research indicates that the development of generative AI will make human labor more productive and lead to more creativity and innovative work behavior (IWB) (Malik et al., 2021; Wijayati et al., 2022).

While existing literature recognizes the impact of generative AI on human behavior and performance, there is a gap in understanding the specific impact of generative AI on individuals' IWB, with no exploration of self-efficacy as a mediating factor. Enhancing your employees' innovative capacities can be very beneficial to an organization looking to acquire a competitive advantage (Shanker et al., 2017; Qawasmeh & Wahab, 2022), therefore knowing the influence of

generative AI on IWB is critical. According to Noy and Zhang's (2023) study, employees who used generative AI reported higher levels of self-efficacy than those who did not. The study by Lin (2023) also suggests that using generative AI can help achieve learning goals. Thus, by giving employees access to this complex and powerful tool, their belief that they can achieve their goals is enhanced. This could be a reason why the use of generative AI can lead to an increase in performance. Apart from the evidence for the direct relationship between the usage of generative AI and the self-efficacy of employees, studies suggest that self-efficacy also leads to more innovative behavior (Momeni et al., 2014; Wei et al., 2020; Dasmo et al., 2022; Hu, 2023). The inclusion of self-efficacy in the model contributes to a better understanding of the strength and direction of the relationship between the use of generative AI and innovative behavior, as well as insight into the psychological process that underpins the transformation of AI interactions into tangible innovative outcomes. Hence, it is interesting to investigate the degree to which self-efficacy mediates the relationship between employee usage of generative AI and IWB.

The hypothesized model, underpinned by the JD-R theory, put forth by this study is that using generative AI affects both IWB and beliefs about one's own efficacy, which in turn will also influence IWB. Previous research has focused on the general impact of generative AI on performance or creativity, but it has not thoroughly investigated the complex relationship between generative AI use, the development of self-efficacy beliefs, and the subsequent display of IWB. The present study will add to the body of literature by proposing the idea that as employees use generative AI, they will internalize cognitive processes, leading to the enhancement of their self-efficacy in generating new ideas and solutions. Implicating that managers can deploy generative AI, such as ChatGPT, to foster self-efficacy and innovation. This research will help understand the cognitive processes that underlie the adoption of generative AI and the ways in which it impacts human behavior. As such, the research question of this study is as follows:

RQ: To what extent does employee use of generative AI affect their IWB, and to what extent is this relationship mediated by self-efficacy?

Theoretical Background

This section will provide an overview of existing literature and theories, as well as a detailed explanation of each construct and potential mechanisms at work.

Generative Artificial Intelligence

Artificial intelligence (AI) is the ability of a machine or computer system to simulate and carry out tasks like learning, problem solving, and logical reasoning that would typically require human intelligence (Morandín-Ahuerma, 2022). It can emulate human and behavioral processes within machines (Berşe et al., 2023). According to Meşe et al. (2023), NLP is a branch of AI that studies the interaction between computers and human language, and it uses computer programs and algorithms to analyze, understand and generate human language. Popular generative AI programs include ChatGPT, Bard, DALL-E, and Midjourney. GPT-3, a generative AI program that merges NLP and deep learning, is starting to exhibit some aspects of general intelligence (Benbya et al., 2020). ChatGPT (Generative Pre-Trained Transformer) is a generative AI-powered NLP chatbot that uses the GPT-3 language model (Floridi & Chiriatti, 2020). ChatGPT can understand and respond to complex questions and commands in natural language thanks to its state-of-the-art capabilities and has, as a result, revolutionized the way we communicate with machines (Meşe et al., 2023). According to Benbya et al. (2020), these advancements in generative AI technologies provide new opportunities for organizations to automate and improve processes. In the modern business world, implementing AI technologies is essential for innovation and efficiency (Cavus et al., 2023).

It is apparent that generative AI technologies are fundamentally reshaping businesses and their processes, and because of their advantages, they can be deployed across an organization's entire value chain (PwC, 2019; Wamba-Taguimdje et al., 2020). Wamba-Taguimdje et al. (2020) argue that generative AI has the potential to improve efficiency, an organization's adaptability, and forecasting while also reducing errors. Generative AI adoption can substantially boost employee work engagement (Wijayati et al., 2022), productivity, self-efficacy, increase quality, reduce time spent on tasks (Noy & Zhang, 2023), and increase flexibility, creativity, and innovation (Malik et al., 2021). Berşe et al. (2023) suggest that generative AI can enhance time management, knowledge and skill levels and enhance educational experiences by personalizing learning opportunities. Thus, it can be concluded that using generative AI has the potential to improve performance at the organizational and process levels.

A theory that could be used to explain the positive effects of using generative AI is the Job Demands-Resources (JD-R) theory. This theory explains how job demands and resources influence job performance through employee well-being and how employees use proactive and reactive work behavior to influence these demands and resources (Bakker et al., 2014; Bakker & Demerouti, 2017; Bakker et al., 2023). Job demands are defined as physical, psychological, social, or organizational aspects of a job that have a psychological or physiological cost (Bakker et al., 2023). Job resources, on the other hand, are defined as physical, psychological, social, or organizational aspects of the job that have motivating potential and can stimulate learning and personal growth while also helping to regulate job demands (Bakker & Demerouti, 2017). According to Bakker et al. (2023), personal resources, such as self-efficacy, have a reciprocal relationship with job resources, implying that employees with more personal resources are expected to have access to more job resources and vice versa.

Research shows that the use of generative AI can provide new and personalized learning opportunities, achieve learning goals (Berşe et al., 2023; Lin, 2023), improve communication (Agathokleous et al., 2023; Meşe et al., 2023), enhance knowledge and skill levels (Berşe et al., 2023), and reduce time spent on tasks (Malik et al., 2021; Noy & Zhang, 2023), all of which could alleviate workload. Therefore, using generative AI can be considered a job resource as it is an aspect of the job that can promote learning and development while assisting in managing job demands. Using generative AI frees up employees' time and resources from mundane tasks and improves their talent by increasing their job learning and allowing them to engage in creativity and innovation in management processes and functions (Malik et al., 2021). Thus, using generative AI frees up more resources, makes resource utilization more efficient (Wamba-Taguimdje et al., 2020) and enables employees to engage in more IWB.

Innovative Work Behavior

As noted earlier, generative AI has the ability to increase IWB in organizations (Malik et al., 2021) as it enables the design of new products, services, manufacturing or organizational processes (Wamba-Taguimdje et al., 2020). IWB is defined as the intentional creation, promotion and application of novel ideas within a job role or organization to improve organizational performance (Janssen, 2004). According to Afsar et al. (2014), it includes thinking about the unfulfilled needs of stakeholders, problems with existing work methods, or solutions to problems that arise due to changing trends. IWB can be seen as a complex, multiple-

stage process where the individual first recognizes a problem and creates new solutions or ideas for it, then promotes and builds support for them, and finally produces an innovation model that can be applied (Carmeli et al., 2006). Seeking to gain a competitive advantage, a number of high-tech companies aim to enhance their employees' IWB (Shanker et al., 2017; Qawasmeh & Wahab, 2022).

According to Verma and Singh (2022), in the future, when generating new ideas and solutions, employees will be guided by AI. They argue that AI, like chatbots, facilitates information processing at a larger level to generate new ideas and solutions, which would not be possible if a human processed the same information. With more resources at their disposal and more effective resource utilization (Malik et al., 2021), generative AI generally enhances job learning and empowers workers to think more creatively and innovatively (Wamba-Taguimdje et al., 2020). By freeing up resources and increasing skills, generative AI enables employees to engage more in IWB (Malik et al., 2021). Using generative AI can thus foster IWB (Wamba-Taguimdje et al., 2020; Malik et al., 2021; Wijayati et al., 2022); therefore, the first hypothesis is as follows:

H1: Employee usage of generative AI has a positive effect on a person's IWB.

Self-Efficacy

Aside from the hypothesized effect on job resource IWB, the current study hypothesizes that using generative AI increases personal resource self-efficacy. Self-efficacy refers to the belief that a person can achieve certain goals (Gist, 1987). The construct is a basis for motivation, a better life and more individual achievements in all aspects of life (Momeni et al., 2014). Self-efficacy has been adopted into the JD-R theory as a personal resource (Mäkikangas et al., 2013) and has a range of benefits for individuals as well as organizations as a whole, such as an increase in performance, perseverance (Bandura, 1997), and IWB (Dasmo et al., 2022).

Various research results show that using generative AI tools has an effect on a person's self-efficacy (Yilmaz & Yilmaz, 2023). Using generative AI and ChatGPT has proven to directly affect students' self-efficacy (Li & Wang, 2021; Huang & Qiao, 2022; Wang et al., 2022). Noy and Zhang (2023) demonstrate that the use of generative AI directly raises self-efficacy in a variety of professions, such as HR professionals, managers, writers, marketeers, and consultants, rather than only for students. With greater resources at their disposal, employees using

generative AI can accomplish learning goals and spend less time on tasks, increasing their belief that they can succeed in their goals.

Proposition four of the JD-R theory (Bakker et al., 2014) states that personal resources and job resources can strengthen each other, implying that having access to job resources increases one's personal resources. By establishing that using generative AI can be considered a job resource and self-efficacy a personal resource, a hypothesis can be formulated. Based on the fourth proposition of the JD-R theory and available literature, this study hypothesizes that the use of generative AI will lead to an increase in self-efficacy. This results in the second hypothesis:

H2: Employee usage of generative AI has a positive effect on a person's self-efficacy.

According to Dasmu et al. (2022), self-efficacy is critical for fostering IWB; their meta-analysis demonstrates that there is a significant positive relationship between self-efficacy and IWB. When someone believes they have what it takes to complete a task, it manifests itself in how they seize opportunities, generate-, promote-, and realize ideas (Dasmu et al., 2022). Which suggests that an individual's IWB can be built on the belief that they are capable of engaging in innovative behavior. Sulistiowati (2018) argues that it is impossible to realize IWB without this self-confidence in their own abilities. Because of this confidence, individuals with high levels of self-efficacy are also more likely to engage in IWB (Newman et al., 2018). In other words, a person is more likely to act in a way that will result in the generation of new ideas when they believe they have the resources and capabilities to fulfill their goals (Momeni et al., 2014; Wei et al., 2020; Hu, 2023). Individuals with low levels of self-efficacy and resources are more likely to perceive challenges and are less well-equipped when confronted with the uncertainty that comes with innovation (Newman et al., 2018). Based on this reasoning, the third hypothesis is as follows:

H3: Self-efficacy has a positive effect on a person's IWB.

The Mediating Effect of Self-Efficacy

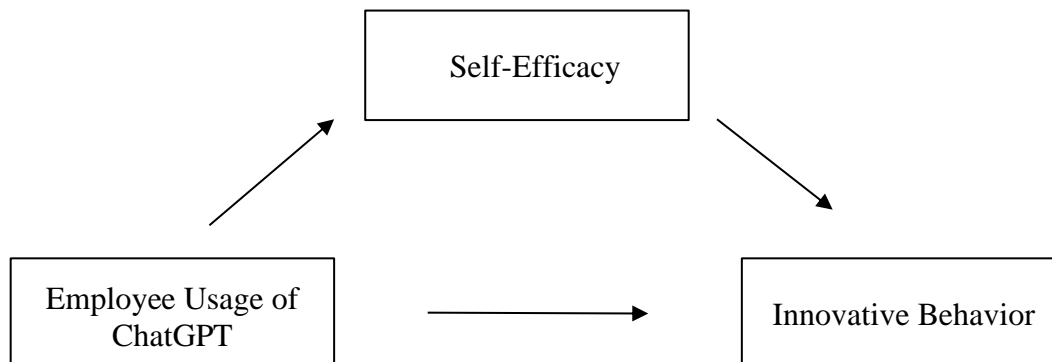
This section highlighted the effects of employees using generative AI on their IWB and self-efficacy, along with how self-efficacy can be seen as a predictor of IWB. Using generative AI will increase employees' self-efficacy by providing them with more resources, freeing up time (Wamba-Taguimdje et al., 2020), coming up with innovative solutions (Verma & Singh, 2022), and assisting them in reaching their learning goals (Berşe et al., 2023; Lin, 2023; Noy & Zhang, 2023). Subsequently, the enhancement of employees' self-efficacy will make them engage in

more innovative thinking as they believe that they are more capable of exhibiting IWB (Momeni et al., 2014; Newman et al., 2018; Wei et al., 2020; Dasmo et al., 2022; Hu, 2023). Self-efficacy is often a mediator variable and has been demonstrated to be a determining factor in the strengthening of the relationship between an independent variable and IWB, according to Dasmo et al.'s (2022) meta-analysis. As a result, the current study hypothesizes that using generative AI influences beliefs about one's own efficacy, which in turn influences IWB, leading to the following hypothesis:

H4: The relationship between employee usage of generative AI and IWB is mediated by a person's self-efficacy.

Figure 1

Conceptual model



Method

The purpose of this study is to shed more light on the impact of employee use of generative AI on their IWB and self-efficacy, as well as the mediating role of self-efficacy in this relationship. This section will give an overview of how the current study is designed in order to answer its research question.

Research Design

The current study employs a quantitative research design and uses cross-sectional data in order to evaluate the relationship between generative AI, IWB and self-efficacy. Cross-sectional data is data gathered from individuals at a single point in time who have been chosen to represent a specific target population (Straits & Singleton, 2018). A questionnaire was used to collect data, with questions based on scales that measure the relevant constructs. The purpose of this study is to explain the relationship between the variables and a potential mediating effect; as such, the nature is explanatory. By definition, explanatory research formally tests relationships and seeks to explain why phenomena occur (Straits & Singleton, 2018).

Sample and Procedure

Data was collected through the social networks of five master students, making it possible to recruit workers from various organizations. To battle the weaknesses of using a non-probability sample, such as investigator bias (Straits & Singleton, 2018), a combination of convenience sampling and the snowball sampling technique was used. Students in the thesis circle reached out to employees through their personal network and an invitation message on LinkedIn. As long as the employees work in an organization and have experience working with generative AI in the workplace, there were no limitations on whether they were recruited to participate. Those who participated were asked to invite someone they knew who used generative AI. The questionnaire was distributed as an online survey, and participation was voluntary and confidential. The survey consisted of different validated scales; the tutor provided the generative AI scale, and students had to search for validated scales that measured their own respective constructs. A power analysis was conducted during the data collection period to determine the appropriate number of respondents for the survey. The calculated number of minimal respondents needed to have an appropriate sample was 126. After eliminating incomplete responses, the actual sample used in this study is $N = 140$, indicating that sample was appropriate to have meaningful results. Of these respondents, 51.4% are male and 44.3% are

female (6 values were missing), with ages ranging from 20 to 62, a mean age of 34, and a standard deviation of 12.93. The data showed the sample was highly educated, with 42.9% of the respondents having completed a university master's or above. 32.1% of the respondents completed a university bachelor, 16.4% had completed an applied sciences bachelor, and 5.9% had upper secondary education or lower.

Instruments

The self-efficacy and IWB scales that were used are displayed in Appendix A.

Employee Usage of Generative AI

This study measured the usage of generative AI by employees using 19 questions on the generative AI scale (Fong, 2023) that consisted of three different dimensions. The three dimensions relevant to this study are: automating demands, augmenting demands, and augmenting instrumental resources. These dimensions were all measured using a five-point Likert scale ranging from 1 (never) to 5 (always).

The sub-dimension of automating demands is concerned with employees using generative AI to proactively automate job demands to minimize their direct involvement in tasks and to gain efficiency. This dimension is measured using seven questions and an example is: ‘At work, I proactively use generative AI to automate repetitive tasks.’

Augmenting demands refers to the process in which employees proactively interact with generative AI to manage job demands, aiming to increase quality and foster creativity in task outcomes. This dimension is measured by using nine questions, an example being: ‘At work, I proactively interact with generative AI to explore innovative approaches for my tasks.’

Augmenting instrumental resources pertains to employees proactively interacting with generative AI to increase work-related knowledge and skills. An example question of this dimension is as follows: ‘At work, I proactively interact with generative AI to acquire work-related knowledge.’ This dimension consists of three questions.

Innovative Work Behavior

The IWB scale ($\alpha = .94$), created by De Jong and Hartog (2010), is used to measure the IWB construct. Based on the theoretical definition in this study, IWB is seen as a comprehensive construct. The questions are measured on a five-point Likert scale (1=never, 5=constantly). An example question is: ‘I generate original solutions for problems’ (De Jong & Hartog, 2010).

Self-Efficacy

The new general self-efficacy scale ($\alpha = .79$) was created by Chen et al. (2001) to assess self-efficacy in organizational research. Questions are measured using a five-point Likert scale (1=strongly disagree, 5=strongly agree). An example question is: ‘I will be able to achieve most of the goals that I have set for myself’ (Chen et al., 2001).

Analysis

IBM SPSS Statistics 28 was used for the processing and analysis of the data. The initial step in the data analysis process was to clean the data. Missing values were examined and recoded as user missing values (coded as 99); as such, these would not influence the analysis. Of the total 174 responses to the survey, 34 were incomplete and thus listwise deleted. There were no reversed items in the scales, so there was no need to reverse the scores. Next, Cronbach's alpha was used to assess the reliability of the various scales, and factor analysis was used to evaluate their validity. In terms of validity, Bartlett's test should be significant (Bartlett, 1954) and the Kaiser Meyer-Olkin Measure of Sampling Adequacy (Kaiser, 1974) recommends accepting values greater than 0.6. In order to strengthen the model and find other variables that might have an impact on the relationship being studied, the variables educational level, gender, and age were controlled for during the analyses. Because people's experiences, technological skills, and adaptability can differ greatly between age groups, age should be taken into account as a control variable (Czaja et al., 2006). Previous research has shown that men and women may have different attitudes towards technology, as men hold more favorable attitudes towards technology use than women (Cai et al., 2017). People who are naturally inclined to learn better are expected to be better suited to handle the complexity of new technologies, according to Agarwal and Prasad (1999); consequently, educational level is also included as a control variable. Additionally, these three variables have been shown to influence the acceptance an individual has of new information technology (Venkatesh et al., 2003) and AI (Xue et al., 2022). In addition, analyses were conducted to verify that the assumptions of multicollinearity, homoscedasticity, linearity, and normality were not broken. Outliers were also investigated. Correlation and regression analyses were conducted in order to test the different hypotheses. Hayes's PROCESS model 4 (2017) was used in order to execute analyses to test the hypothesized model. Bootstrapping was used to assess the significance of the mediation effect 5000 times, as it is one of the more valid and powerful approaches for evaluating intervening variable effects and requires less unrealistic assumptions than the Sobel test (Hayes, 2009).

Results

The initial step in the statistical analysis was to investigate all the descriptive statistics and correlations among variables relevant to the current study. Self-efficacy is positively correlated with the use of generative AI ($r = .02, p = .83$), but this effect is not significant. Additionally, IWB is positively correlated to both the use of generative AI ($r = .20, p < .05$) and self-efficacy ($r = .31, p < .05$). It is important to note that out of the control variables, only age had a significant negative correlation with the use of generative AI ($r = -.27, p < .01$). Table 1 provides an overview of the descriptive statistics as well as all of the calculated correlations. An analysis of standard residuals revealed that the data had no outliers (Std. Residual Min = -2.30, Std. Residual Max = 2.24).

Table 1

Descriptive Statistics and Correlations for Study Variables

Variable	<i>n</i>	<i>M</i>	<i>SD</i>	1	2	3	4	5	6
1. Generative AI Usage	140	2.48	0.82	—					
2. Self-Efficacy	140	3.88	0.52	.02	—				
3. Innovative Work Behavior	140	3.29	0.71	.20*	.31**	—			
4. Age	137	33.68	12.93	-.27**	-.14	-.00	—		
5. Gender ^a	134	0.46	0.50	.09	-.04	-.01	-.08	—	
6. Educational Level ^b	136	5.13	0.99	-.10	.15	.13	.23**	.06	—

^a 0 = Male and 1 = Female.

^b With higher scores indicating a higher level of education completed.

* $p < .05$. ** $p < .01$.

After the initial step in the analysis, a reliability and factor analysis was done to ensure the construct validity, internal consistency and reliability of the scales. All of the scales presented high reliability, which can be observed in Appendix B. Bartlett's test is significant for the three scales ($p < 0.1$), and the Kaiser Meyer-Olkin Measure reports values of .91, .85, and .87. The generative AI scale extracted three factors, the self-efficacy scale one factor, and the IWB scale three factors. The IWB scale extracted multiple dimensions, explaining 51.27%, 11.37%, and 10.07% in variance, in contrast to the literature it was derived from. De Jong and Hartog (2010)

ultimately chose on one dimension for the IWB scale, as there was little support for multiple dimensions.

Tests to determine whether the data met the assumption of collinearity revealed that multicollinearity was not an issue. By using scatterplots and histograms, the assumptions of normality and homoscedasticity were checked, showing that the data met the assumptions of homogeneity of variance and linearity. Since age, gender and educational level are predictors of the adoption of technology and AI (Venkatesh et al., 2003; Xue et al., 2022), they were used as covariates in the analysis. Table 2 presents the results of Hayes' PROCESS analysis (see Appendix C for full output). The first step in the mediation analysis is to test the direct relationship between the independent and dependent variables. This would imply that there is a positive relationship between generative AI usage and IWB. As shown in Table 2, the relationship between these two variables is positively significant in model 1 ($b = .25; p < .01$). Therefore accepting the first hypothesis.

The second step in the mediation analysis was to examine the direct effect between the independent variable and the mediator; this is formulated in Hypothesis 2. This hypothesis suggests that there is a positive relationship between generative AI usage and self-efficacy. Looking at Table 2, model 2 shows that there is a positive relationship, but this is not significant ($b = .02; p = .69$). Implying that the second hypothesis is rejected. The next step is to evaluate the relationship between the mediator and the dependent variable. Hypothesis 3 of this study implies that self-efficacy positively affects a person's IWB. The third model confirms this, as self-efficacy has a significant positive relationship with IWB ($b = .36; p < .01$). The third hypothesis is thus accepted.

For the fourth and final step in the mediation analysis, the mediation effect was evaluated. The fourth hypothesis stated that self-efficacy mediates the relationship between generative AI usage and IWB. Bootstrapping was used to assess the significance of the mediation effect. Looking at the indirect effect, it can be concluded that the mediation effect ($b = .01, SE = .02, 95\% CI [-.04, .06]$) is not significant. The Sobel test confirms this, as it is also non-significant, thereby rejecting the fourth hypothesis. It is important to note that out of the control variables, only age and educational level have a significant relationship with self-efficacy. None of the control variables have a significant relationship with IWB. This will be discussed further in detail in the upcoming limitations section.

Table 2
Output PROCESS Analysis

Variables	Model 1 (Outcome IWB)					Model 2 (Outcome Self-Efficacy)				
	<i>b</i>	Se	<i>p</i>	LLCI	ULCI	<i>b</i>	Se	<i>p</i>	LLCI	ULCI
Generative AI Usage	.25**	.08	.00	.11	.40	.02	.06	.69	3.05	4.23
Age	.00	.01	.75	-.01	.01	-.01*	.00	.04	-.02	-.00
Educational Level	.11	.06	.06	-.01	.23	.09*	.05	.04	.00	.18
Gender	-.19	.12	.11	-.42	.05	-.07	.09	.44	-.24	.11
R ²	.11**					.06				
F-test	3.99**					1.99				
Model 3 (Outcome IWB)										
Variables	<i>b</i>	Se	<i>p</i>	LLCI	ULCI					
Generative AI Usage	.25**	.07	.00	.10	.39					
Age	.00	.01	.36	-.01	.01					
Educational Level	.08	.06	.18	-.04	.20					
Gender	-.17	.12	.15	-.39	.06					
Self-Efficacy	.36**	.11	.00	.14	.59					
R ²	.18**									
F-test	5.43**									

n = 140 *p < .05. **p < .01.

Discussion

The objective of the current study was to explore the relationship between the use of generative AI by employees and the innovative work behaviors that they engaged in. More specifically, drawing from the JD-R theory (Bakker et al., 2014), this study investigated whether this relationship is mediated by a person's self-efficacy. Four hypotheses were developed. The first hypothesis stated that the use of generative AI would positively affect IWB, which was accepted. Indicating that using generative AI enables employees to engage more in IWB. Hypothesis 2 suggests that employee usage of generative AI positively affects a person's self-efficacy. This hypothesis was rejected based on the non-significant result of the analysis. Which demonstrates that generative AI use does not boost employee self-efficacy. The third hypothesis said that a person's self-efficacy positively influenced their IWB. This hypothesis was accepted, implying that an individual's IWB can be founded on the belief that they are capable of engaging in IWB. The final hypothesis of this study investigated the possible mediating effect of self-efficacy in the relationship between generative AI usage and IWB, which was refuted. Indicating that generative AI does not have a positive effect on employee IWB through the increase of self-efficacy. Despite the reasoning behind including age, gender, and educational level as control variables, almost all had no significant relationship with IWB or self-efficacy. Only the control variables, age and educational level, had a significant relationship with self-efficacy.

The results demonstrated significant direct relationships between the use of generative AI and IWB, as well as self-efficacy. Which suggests that using generative AI fosters IWB and that a person engages in more IWB when they believe they are able to fulfill their goals. The direct relationship between generative AI usage and self-efficacy, however, was not statistically significant. Contrary to the reasoning based on proposition four of the JD-R theory (Bakker et al., 2014), the results did not support the belief that personal resources (self-efficacy) and job resources (generative AI use) strengthen each other. The relationship was positive, but it was not statistically significant. A possible explanation may be that using generative AI may provide more job resources, but it may also bring on new challenges or stresses that offset the anticipated rise in self-efficacy. Suggesting that there may be a period during which employees have to learn how to use generative AI optimally.

The mediating effect of self-efficacy was not significant, implying that increasing employees' self-efficacy through the use of generative AI will not result in more innovative

thinking. A possible explanation for this could be that the self-efficacy scale is biased, as people are more likely to give the correct answer and rate themselves highly on it. The mean of this scale was 3.88 out of 5 and had a standard deviation of 0.52, which shows these high scores. An early indicator of this result was the non-significant correlation between generative AI usage and self-efficacy. A theoretical reason may be that self-efficacy is a domain-specific construct and can vary significantly across different tasks and situations (Jungert et al., 2014). The use of generative AI may increase task-specific self-efficacy (for example, confidence in using AI tools), but this may not convert into general self-efficacy in terms of performance or innovative behavior.

Theoretical Implications

The findings of this study present a number of theoretical implications for (generative) AI literature. It contributes to an understanding of the outcomes of using generative AI in an organizational context. The implications of this study are threefold.

First of all, the results contribute to our understanding of the effect that generative AI use has on an individual's IWB. The findings of the current study are consistent with the results of Wamba-Taguimdje et al. (2020), Malik et al. (2021), and Wijayati et al. (2022). According to these three studies, using generative AI fosters IWB by freeing up and increasing resources and skills, thus enabling generative AI employees to engage more in IWB. This study reinforces the notion by Cavus et al. (2023) that implementing AI technologies is crucial for innovation in the modern business world. According to Cavus et al. (2023), AI technologies are essential to the fundamental business plans of companies that want to remain inventive and competitive, not just supplemental tools. By providing empirical evidence, this study emphasizes the significance of implementing generative AI in organizational processes to encourage new levels of productivity, creativity, and innovation. The current study sets the stage for the emerging research on generative AI use and its innovative behavior, by introducing the mediating effect of self-efficacy. This study emphasizes the complexities of the relationship between generative AI use and potential results by contradicting existing theories' reasoning.

Furthermore, the findings can be interpreted through the lens of the JD-R theory (Bakker et al., 2014). Earlier in this study, it was proposed that having access to and using generative AI could be viewed as a job resource for employees. By freeing up employees' time and mental energy, using generative AI in the workplace can assist in managing job demands and promoting

learning and development (Berşe et al., 2023; Lin, 2023), which can then be redirected towards more innovative and creative thinking. By testing the relationship between AI usage and IWB, the findings of this study provide some evidence for the notion that, by using generative AI, job resources will increase, creating an ideal environment for engaging in IWB.

Additionally, the current study contributes to our understanding of the relationship between self-efficacy and IWB. The findings add to the already established positive relationship between the variables (e.g., Momeni et al., 2014; Newman et al., 2018; Wei et al., 2020; Hu, 2023). These earlier studies have repeatedly shown that higher levels of self-efficacy lead to an increase in IWB, highlighting the significance of self-belief in promoting innovation in the workplace. The meta-analysis by Dasmo et al. (2022) examined seven studies that investigated the relationship between self-efficacy and IWB. This study supports their findings, which showed a significant and positive relationship between the two variables. They argue that, based on their meta-analysis, self-efficacy is a mediator in many different relationships. As stated in their study, self-efficacy often determines how strongly an independent variable and IWB are related (Dasmo et al., 2022). This notion, however, is not supported by the findings, which show that self-efficacy does not mediate the relationship between generative AI use and IWB.

The unexpected lack of relationship between generative AI use, self-efficacy, and its mediating effect on IWB also contradicts the logic based on the fourth proposition of the JD-R theory. This finding also has a theoretical implication for the context of the psychological processes that underpin the transformation of AI interactions into tangible outcomes. This fourth proposition states that personal resources and job resources can reinforce each other, meaning that having access to job resources boosts one's personal resources (Bakker et al., 2014). Nevertheless, the study's findings contradict this theoretical prediction. The lack of a positive relationship between the use of generative AI and an increase in self-efficacy challenges the assumption that generative AI, as a job resource, would naturally increase employees' self-efficacy. This disparity implies that the relationship between AI technologies and psychological elements such as self-efficacy may be more complex than previously anticipated. While generative AI may provide job resources by increasing efficiency and reducing workload, it may also introduce new challenges or stressors that counteract the expected increase in self-efficacy. A possible challenge could be that using generative AI tools can be complex, require certain skills and therefore not lead to self-efficacy. The incorporation of generative AI into the

workplace is still in its early stages, so there may be an adjustment period while employees learn how to use the technology to its full potential (Peregrine, 2023). During this learning curve, employees might feel lost without the proper support and experience lower levels of self-efficacy.

Limitations and Suggestions for Future Research

Regarding the limitations of this study, several have been identified. First of all, the selected research design was a cross-sectional study. This choice already has drawbacks. This design collects data at one point in time and thus needs less time to be executed. A disadvantage of this design, however, is that causality is very hard to determine, and it has an increased chance of common method bias, raising questions surrounding the validity of the design (Rindfleisch et al., 2008). To decrease the bias of a cross-sectional design, a longitudinal design could be chosen to increase generalizability and casual inferences. Given that time was the most important factor in selecting a cross-sectional design, a longitudinal design is recommended for future research to overcome this limitation. A longitudinal design will also allow researchers to investigate whether employees' ability to work effectively with generative AI improves over time and possibly leads to better outcomes. This way, future research can take the learning curve associated with generative AI into consideration and examine its effect.

Additionally, a limitation can be identified regarding the collection of the data. The data was collected mainly through convenience sampling. As a result, the sample that was collected might not be representative of the population. This also raises concerns regarding the generalizability of this study. There may also be bias present because the participants are presumably people who are already interested in innovation and are familiar with using generative AI. As also evident in the high educational level score of the sample. Because of this selectivity, it is difficult to generalize the findings to the larger population, as the sample may not accurately reflect the diversity found in the workforce as a whole. As a result, the findings of this study may not be applicable to all employees. Furthermore, because data collection proved to be challenging, the survey was limited to self-reported items. Which is naturally susceptible to social desirability bias (Austin et al., 1998). If a coworker or supervisor rated the items, this bias could be reduced. This, along with random sampling, will serve as recommendations for future research.

Further research is needed to explore and understand the relationship between generative AI use and self-efficacy. The contrasting findings with the literature suggest that there is more to this relationship, and an explanation may be found within the context that should be investigated. Another limitation of this study was that it did not include contextual variables, which is suggested for future research on the relationship. Including contextual variables allows researchers to identify contextual factors that may either strengthen or weaken the relationship. Future studies could, for example, include AI training or organizational support, in order to examine the effect this has on using AI. Furthermore, further research could concentrate on self-efficacy as a moderator in this relationship since there is already a known relationship between self-efficacy and IWB, and this study found no evidence for self-efficacy as a mediator in the relationship between generative AI use and IWB. Investigating self-efficacy as a moderator could reveal how different levels of self-efficacy influence the relationship between using generative AI and IWB. Individuals with high self-efficacy, for example, might be more likely to effectively exploit generative AI, thereby increasing their innovative capacities, whereas those with low self-efficacy may struggle to do so.

Practical Implications

This study offers several practical implications for organizations looking to integrate generative AI and enhance IWB among employees. One key implication is that raising self-efficacy will result in more innovative behavior. As a result, companies seeking to improve IWB may also seek to develop a workforce that is more self-efficacious. The second implication indicates that businesses deploying generative AI as a tool for their employees can expect to see not only enhanced productivity but also a more engaged and innovative workforce, ultimately leading to sustained competitive advantages in their respective industries (Qawasmeh & Wahab, 2022). Employees can gain and free up more resources by having access to generative AI, which enables them to think more innovatively. Finally, employees should receive proper support and training to enhance their skills in using generative AI. Employees will be more productive and less likely to feel lost when using generative AI. Consequently, employees will have a shorter learning curve and adjustment period and will feel more at ease utilizing generative AI, leading to greater self-efficacy. To conclude, rather than replacing humans, research indicates that the growth of generative AI would make human labor more productive, give them access to more

resources, and lead to increased creativity and innovative behavior (Malik et al., 2021; Wijayati et al., 2022).

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Appendix A

IWB and Self-Efficacy Scale

Innovative Work Behavior:

Innovative work behaviour ($\alpha = .941$). These questions were measured on a five point Likert scale (1= never, 5= constantly) (De Jong & Hartog, 2010)

1. I pay attention to issues that are not part of his daily work.
2. I wonder how things can be improved.
3. I search out new working methods, techniques or instruments.
4. I generate original solutions for problems.
5. I find new approaches to execute tasks.
6. I make important organizational members enthusiastic for innovative ideas.
7. I attempt to convince people to support an innovative idea.
8. I systematically introduce innovative ideas into work practices.
9. I contribute to the implementation of new ideas.
10. I put effort in the development of new things.

Self-Efficacy:

New general self-efficacy scale ($\alpha = .79$) These questions were measured on a five point Likert scale: (1) strongly disagree, (2) disagree, (3) neutral, (4) agree, (5) strongly agree (Chen et al., 2001)

1. I will be able to achieve most of the goals that I have set for myself.
2. When facing difficult tasks, I am certain that I will accomplish them.
3. In general, I think that I can obtain outcomes that are important to me.
4. I believe I can succeed at most any endeavor to which I set my mind.
5. I will be able to successfully overcome many challenges.
6. I am confident that I can perform effectively on many different tasks.
7. Compared to other people, I can do most tasks very well.
8. Even when things are tough, I can perform quite well.

Appendix B

Reliability and Factor Analysis of Different Scales

Generative AI Scale

Table B1

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardize d Items	N of Items
,945	,946	19

Table B2

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Q19_1	44,51	216,870	,657	,646	,943
Q19_2	44,99	218,762	,645	,611	,943
Q19_3	44,46	215,646	,632	,512	,943
Q19_4	44,21	218,367	,624	,581	,943
Q19_5	44,27	215,883	,690	,605	,942
Q19_6	45,17	224,186	,572	,486	,944
Q19_7	45,53	225,776	,527	,477	,945
Q20_1	44,24	215,264	,718	,627	,942
Q20_2	44,87	216,991	,736	,644	,941
Q20_3	44,52	214,812	,726	,657	,942
Q20_4	43,72	215,454	,661	,562	,943
Q20_5	45,40	224,012	,646	,550	,943
Q20_6	44,46	215,804	,738	,620	,941
Q20_7	44,70	215,650	,748	,683	,941
Q20_8	44,28	213,008	,732	,688	,941
Q20_9	44,41	213,079	,753	,720	,941
Q21_1	45,04	220,049	,641	,560	,943
Q21_2	44,47	216,970	,671	,714	,943
Q21_3	44,54	218,811	,643	,635	,943

Table B3
Inter-Item Correlation Matrix

	Q19_1	Q19_2	Q19_3	Q19_4	Q19_5	Q19_6	Q19_7	Q20_1	Q20_2	Q20_3	Q20_4	Q20_5	Q20_6	Q20_7	Q20_8	Q20_9	Q21_1	Q21_2	Q21_3
Q19_1	1,000	,640	,564	,527	,439	,482	,350	,527	,465	,522	,532	,389	,445	,469	,410	,499	,460	,339	,346
Q19_2	,640	1,000	,436	,348	,497	,508	,476	,426	,495	,462	,417	,566	,531	,434	,417	,409	,462	,438	,394
Q19_3	,564	,436	1,000	,457	,437	,379	,368	,573	,486	,476	,599	,353	,465	,433	,439	,482	,356	,421	,348
Q19_4	,527	,348	,457	1,000	,563	,285	,409	,572	,502	,416	,478	,374	,380	,475	,500	,427	,413	,451	,410
Q19_5	,439	,497	,437	,563	1,000	,518	,474	,469	,507	,482	,437	,420	,579	,484	,534	,514	,412	,565	,520
Q19_6	,482	,508	,379	,285	,518	1,000	,495	,364	,417	,412	,400	,455	,497	,380	,415	,490	,354	,290	,283
Q19_7	,350	,476	,368	,409	,474	,495	1,000	,339	,379	,388	,301	,507	,375	,314	,376	,361	,397	,292	,294
Q20_1	,527	,426	,573	,572	,469	,364	,339	1,000	,608	,637	,611	,399	,535	,599	,520	,527	,477	,508	,409
Q20_2	,465	,495	,486	,502	,507	,417	,379	,608	1,000	,708	,519	,516	,554	,586	,498	,557	,568	,513	,506
Q20_3	,522	,462	,476	,416	,482	,412	,388	,637	,708	1,000	,577	,432	,584	,618	,554	,594	,454	,441	,478
Q20_4	,532	,417	,599	,478	,437	,400	,301	,611	,519	,577	1,000	,398	,541	,499	,505	,566	,333	,366	,335
Q20_5	,389	,566	,353	,374	,420	,455	,507	,399	,516	,432	,398	1,000	,554	,534	,493	,502	,475	,501	,491
Q20_6	,445	,531	,465	,380	,579	,497	,375	,535	,554	,584	,541	,554	1,000	,626	,637	,636	,475	,499	,498
Q20_7	,469	,434	,433	,475	,484	,380	,314	,599	,586	,618	,499	,534	,626	1,000	,676	,740	,544	,526	,569
Q20_8	,410	,417	,439	,500	,534	,415	,376	,520	,498	,554	,505	,493	,637	,676	1,000	,743	,433	,601	,566
Q20_9	,499	,409	,482	,427	,514	,490	,361	,527	,557	,594	,566	,502	,636	,740	,743	1,000	,516	,495	,514
Q21_1	,460	,462	,356	,413	,412	,354	,397	,477	,568	,454	,333	,475	,475	,544	,433	,516	1,000	,604	,543
Q21_2	,339	,438	,421	,451	,565	,290	,292	,508	,513	,441	,366	,501	,499	,526	,601	,495	,604	1,000	,752
Q21_3	,346	,394	,348	,410	,520	,283	,294	,409	,506	,478	,335	,491	,498	,569	,566	,514	,543	,752	1,000

Table B4
KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,918
Bartlett's Test of Sphericity	Approx. Chi-Square	1697,310
	df	171
	Sig.	,000

Self-Efficacy Scale

Table B5

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,869	,871	8

Table B6

Inter-Item Correlation Matrix

	Q13_1	Q13_2	Q13_3	Q13_4	Q13_5	Q13_6	Q13_7	Q13_8
Q13_1	1,000	,526	,356	,304	,437	,491	,306	,334
Q13_2	,526	1,000	,532	,546	,418	,520	,298	,408
Q13_3	,356	,532	1,000	,519	,484	,419	,373	,494
Q13_4	,304	,546	,519	1,000	,613	,469	,420	,374
Q13_5	,437	,418	,484	,613	1,000	,556	,485	,437
Q13_6	,491	,520	,419	,469	,556	1,000	,519	,587
Q13_7	,306	,298	,373	,420	,485	,519	1,000	,577
Q13_8	,334	,408	,494	,374	,437	,587	,577	1,000

Table B7

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Q13_1	27,16	14,095	,527	,379	,863
Q13_2	27,24	13,236	,634	,515	,852
Q13_3	27,02	13,877	,623	,438	,854
Q13_4	27,25	13,023	,633	,518	,852
Q13_5	27,10	13,558	,678	,523	,848
Q13_6	27,02	13,330	,706	,539	,845
Q13_7	27,36	13,483	,575	,430	,859
Q13_8	27,14	13,476	,626	,496	,853

Table B8
KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,847
Bartlett's Test of Sphericity	Approx. Chi-Square	467,208
	df	28
	Sig.	,000

Innovative Work Behavior Scale
Table B9
Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,888	,886	10

Table B10
Inter-Item Correlation Matrix

	Q25_1	Q25_2	Q25_3	Q25_4	Q25_5	Q25_6	Q25_7	Q25_8	Q25_9	Q25_10
Q25_1	1,000	,329	,092	,071	,051	,225	,233	,145	,269	,139
Q25_2	,329	1,000	,541	,417	,390	,384	,414	,299	,315	,277
Q25_3	,092	,541	1,000	,516	,515	,480	,454	,444	,407	,455
Q25_4	,071	,417	,516	1,000	,781	,499	,488	,587	,450	,450
Q25_5	,051	,390	,515	,781	1,000	,547	,513	,610	,446	,424
Q25_6	,225	,384	,480	,499	,547	1,000	,735	,633	,544	,524
Q25_7	,233	,414	,454	,488	,513	,735	1,000	,598	,536	,517
Q25_8	,145	,299	,444	,587	,610	,633	,598	1,000	,626	,616
Q25_9	,269	,315	,407	,450	,446	,544	,536	,626	1,000	,697
Q25_10	,139	,277	,455	,450	,424	,524	,517	,616	,697	1,000

Table B11
Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Q25_1	30,05	46,307	,228	,196	,902
Q25_2	29,02	43,503	,519	,412	,883
Q25_3	29,39	41,478	,610	,469	,878
Q25_4	29,48	40,827	,676	,649	,873
Q25_5	29,54	40,380	,678	,666	,873
Q25_6	29,81	39,178	,733	,623	,868
Q25_7	29,54	39,718	,718	,599	,870
Q25_8	30,01	39,633	,733	,612	,869
Q25_9	29,62	40,611	,684	,583	,872
Q25_10	29,51	40,554	,650	,567	,875

Table B12
KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,872
Bartlett's Test of Sphericity	Approx. Chi-Square	728,935
	df	45
	Sig.	,000

Appendix C

Full Output Hayes' PROCESS Analysis

Run MATRIX procedure:

***** PROCESS Procedure for SPSS Version 3.5.3 *****

Written by Andrew F. Hayes, Ph.D. www.afhayes.com

Documentation available in Hayes (2018). www.guilford.com/p/hayes3

Model : 4

Y : IWB

X : AI

M : SelfEff

Covariates:

Age EL Gender

Sample

Size: 133

OUTCOME VARIABLE:

SelfEff

Model Summary

R	R-sq	MSE	F	df1	df2	p
,2420	,0586	,2563	1,9911	4,0000	128,0000	,0997

Model

	coeff	se	t	p	LLCI	ULCI
constant	3,6405	,2987	12,1888	,0000	3,0495	4,2315
AI	,0222	,0563	,3941	,6941	-,0892	,1335
Age	-,0076	,0036	-2,1027	,0375	-,0148	-,0004
EL	,0937	,0457	2,0524	,0422	,0034	,1840
Gender	-,0686	,0888	-,7722	,4414	-,2442	,1071

OUTCOME VARIABLE:

IWB

Model Summary

R	R-sq	MSE	F	df1	df2	p
,4195	,1760	,4246	5,4258	5,0000	127,0000	,0001

Model

	coeff	se	t	p	LLCI	ULCI
constant	,8306	,5650	1,4699	,1441	-,2875	1,9487
AI	,2455	,0725	3,3878	,0009	,1021	,3889
SelfEff	,3604	,1138	3,1681	,0019	,1353	,5855
Age	,0043	,0047	,9034	,3680	-,0051	,0137
EL	,0802	,0597	1,3422	,1819	-,0380	,1983
Gender	-,1645	,1145	-1,4361	,1534	-,3911	,0622

***** TOTAL EFFECT MODEL *****

OUTCOME VARIABLE:

IWB

Model Summary

R	R-sq	MSE	F	df1	df2	p
,3330	,1109	,4546	3,9913	4,0000	128,0000	,0044

Model

	coeff	se	t	p	LLCI	ULCI
constant	2,1426	,3977	5,3869	,0000	1,3556	2,9295
AI	,2535	,0749	3,3828	,0010	,1052	,4018
Age	,0015	,0048	,3190	,7503	-,0080	,0111
EL	,1139	,0608	1,8738	,0632	-,0064	,2342
Gender	-,1892	,1182	-1,6001	,1120	-,4231	,0448

***** TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y

Total effect of X on Y

Effect	se	t	p	LLCI	ULCI	c_ps	c_cs
,2535	,0749	3,3828	,0010	,1052	,4018	,3601	,2946

Direct effect of X on Y

Effect	se	t	p	LLCI	ULCI	c'_ps	c'_cs
,2455	,0725	3,3878	,0009	,1021	,3889	,3487	,2853

Indirect effect(s) of X on Y:

	Effect	BootSE	BootLLCI	BootULCI
SelfEff	,0080	,0241	-,0384	,0606

Normal theory test for indirect effect(s):

	Effect	se	Z	p
SelfEff	,0080	,0214	,3732	,7090

Partially standardized indirect effect(s) of X on Y:

	Effect	BootSE	BootLLCI	BootULCI
SelfEff	,0114	,0343	-,0539	,0861

Completely standardized indirect effect(s) of X on Y:

	Effect	BootSE	BootLLCI	BootULCI
SelfEff	,0093	,0276	-,0444	,0694

***** ANALYSIS NOTES AND ERRORS *****

Level of confidence for all confidence intervals in output:

95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals:

5000

----- END MATRIX -----