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Empirical Insights Into AI Personalization's Role in Enhancing Employee Retention Amid Privacy Challenge

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Abstract: The development of Artificial Intelligence (AI) transforms the dynamics of workforce following the increase of remote working in the aftermath of the pandemic. Operational efficiency, workforce experience and retention are yet to be established conclusively. These are some of the questions that AI-based personalisation offers. Nonetheless, the privacy and the trust are put at stake with this AI personalization. The given study is the first one to develop an integrated framework that includes Protection Motivation Theory (PMT), Unified Theory of Acceptance and Use of Technology (UTAUT2), and Self-Determination Theory (SDT) to examine the effects of AI-personalization on the engagement of employees, their willingness to change, and retention. It includes privacy concern as a moderating variable, which makes it relevant to an organization and expands the existing discussions that were confined to the consumer setting. Based on Survey information of 322 out of 463 professionals in India who are currently on remote working. Smart PLS4 assists in the analysis of the current study using SEM-PLS. The outcome and the findings reveal that there is a direct hypothesis support and it also indicates a new, multi-level based framework of comprehending AI integration and retention that could be utilized in global workforce management. Practical implications of the study state that it is not merely the application of AI personalization to the workforce, but it also requires considering the issue of privacy to maintain the trust of the employees, and it will lead to retaining the talent of the organization.

Keywords: AI Personalization, Remote Work, Employee Engagement, Employee Retention, Privacy Concerns

1. Introduction

Following the COVID-19 pandemic, remote work dynamics is quickly becoming popular in the world and the previous workforce has turned into an accelerator of digitization. As a result of developments in the sphere of Artificial Intelligence (AI), remote work, which can also be referred to as e-working, has been made the cornerstone of modern working culture (Kylili *et al.*, 2025; Gkinko and Elbanna, 2023; McPhail *et al.*, 2024). As can be considered, remote work is already expected to grow at a 23.8% compound annual growth rate (CAGR) by 2027, and more than 2.2 million professionals are already at work (StartUs Insights, 2025). Nevertheless, high employee turnover is detrimental to organizations (Galanis *et al.*, 2024; Mah *et al.*, 2025). Remote work has been embraced by several organizations in India particularly the IT industry as firms aim at saving money and flexibility (Raj *et al.*, 2023). But such conversion is accompanied by high rates of employee turnover. The attrition rate in companies such as Wipro was 15.3% in the 3rd quarter of FY 2024 (NDTV Profit, 2024) and Tech Mahindra reported the attrition rate was 15% in the 4th quarter of FY 2023 (Mint, 2023). The remote IT industry experiences high employee turnover, which may lead to high costs in recruiting and training employees, as well as project continuity, innovation and client satisfaction. In addition, remote workers are usually isolated and unsupported, which results in disengagement (Teepapal, 2025). Thus, organizations are concerned with approaches that can improve the productivity and the well-being of employees in the digital space of mediation (Aulia and Lin, 2025; Kaur and Mittal, 2020; Zapata-Cantu,

2022). The personalization strategies can be used to improve retention and decrease turnover rates by fulfilling the employee's needs, including career development program tailored to the distinct needs of the employees, work-life balance, and by identifying activities that can alleviate the situation (Ghani *et al.,* 2022; Huang *et al.*, 2023; Saiyed *et al.,* 2025). As the environment is changing to be remote, AI-based personalization is becoming a reality since it improves operational efficiency and customized experience to individual employees, which makes the workplace more supportive and engaging (Aulia and Lin, 2025; Ameen *et al.,* 2022). Although these advantages exist, the gap in the knowledge of AI personalization in a remote workplace is quite wide (Blömker and Albrecht, 2025; Saks, 2022; Tkalčič and Ferwerda, 2025). Necula *et al.* (2024) and Zhai *et al.* (2024) took the concept of personalization and AI use to the employee engagement level, but the studies do not specifically mention retention in a remote workplace or do not take into account the joint cognitive, technical, and motivational processes that influence employee responses (Afroogh *et al.*, 2024; Khalid and Nawab, 2018; Martin and Zimmermann, 2024). Although there is increased interest in AI personalization, a small amount of research has been done on trust, technical competence, and engagement mechanisms within a single model (Maier and Klotz, 2022). Thus, our research adds value to the existing body of knowledge by 1) making PMT, UTAUT2, and SDT interact to form a multi-level construct, 2) analytically examining the role of AI personalization in employee trust, competence, and engagement, and 3) adding privacy concerns as a moderator.

The extension of this research will offer the following research objectives; the research question seeks to find out the effect of AI-driven personalization in remote work environments on employee retention. The paper goes further to investigate the privacy issues surrounding AI-driven personalization in remote working, and how the issues mediate the effect of AI-driven personalization and retention of employees. The existing research is a synthesis of Protection Motivation Theory (PMT), Unified Theory of Acceptance and Use of Technology (UTAUT2), and Self-Determination Theory (SDT) offering a holistic approach to the idea of AI personalization in remote working and its ability to boost retention (Neves *et al.,* 2025; Venkatesh *et al.,* 2012). PMT investigates the issue of employee perception and tries to suggest that employees consider potential threats, on of which is the invasion of privacy, upon the implementation of an AI system, which affects their readiness to use personalized technologies. UTAUT2 is also the best at AI adoption where performance expectancy and effort expectancy determine adoption behavior, which implies that employees are more inclined to use AI when they consider it to have tangible benefits, whereas SDT focuses on the importance of meeting the intrinsic necessities collectively, thus leading to higher levels of engagement and retention through competence, autonomy, and relatedness (Deci and Ryan, 1985; Rogers, 1975; Venkatesh *et al.*, 2012). Recent empirical evidence supports this theoretical perspective, showing that when workplace conditions align with SDT constructs and enhance intrinsic motivation, employees demonstrate stronger discretionary and pro-organizational behaviors, such as organizational citizenship. The combination of these frameworks will lead to a deeper insight into the behavioral, cognitive, and emotional mechanisms that underlie the concept of AI personalization in remote working. Since the majority of previous research regarding AI personalization was based on the Western setting, the study of the Indian IT industry offers certain peculiarities concerning the culturally specific features of remote working via digital platforms. The research has a contribution to organizations in that it provides information on the implementation of AI personalization in remote work to boost retention. It helps to establish a more sustainable work environment, work-life balance and more inclusive e-workplace. This will also enable organizations to retain best talent that will help them achieve long term success of the business and economic development. Additionally, the rest of the paper has a literature review in section 2, methodology in section 3, results in section 4, discussion in section 5, conclusion, limitations and future research in section 6.

2. Literature Review

2.1. Remote Work and AI Personalization

Remote working and AI customization. Remote work has become a trend after the COVID-19 epidemic, and it has broadened the workplace dynamics. People are highly inclined towards the remote work because of its flexibility and less time spending on traveling (McPhail *et al.,* 2024). It is also, what enables individuals to adjust their working environment, which results in increased productivity and job satisfaction. Nevertheless, it also poses some problems, such as the inability to be engaged and have a consistent organizational framework (Zapata-Cantu, 2022). AI is coming up in nearly every area of the working place. The concept of AI-induced personalization is the idea that it is

possible to adjust the working experience according to the work preferences and behaviors using technologies (Nwanna *et al.,* 2025; Rashid and Kausik, 2024). It primarily entails individualised task placement, customisable learning prospect, and individualised feedback system. This kind of personalization is designed to increase the engagement of employees, their satisfaction, and overall performance (Maier and Klotz, 2022). Remote work can be made easier because AI can offer customized assistance, promote better interaction, and offer continuous learning, which facilitates enhanced employee engagement (Aulia and Lin, 2025).

2.2. Theoretical Framework

Multiple theories have been used to study the adoption of AI, among them being the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2). With UTAUT2, there is complete concentration on the acceptance and sustainable use of technology. The concept of AI-personalization is in line with theories because it is expected to improve work performance due to customized sustenance (Neves *et al.,* 2025; Venkatesh *et al.,* 2012; Gkinko and Elbanna, 2023). Trust in AI systems is an important element in remote working environment to sustain the use and acceptance of technology. Another model of technology adoption is the Technology Acceptance Model (TAM), which refers to the acceptance of technology by the users as a result of their faith in the convenience and usefulness of the technology. Personalized assistance can help AI personalization to increase the perceived usefulness (Davis, 1989; Teepapal, 2025). The present paper attempts to define AI-personalization as the major cause of employee engagement and retention, primarily in remote work setting. To transmit behavioral understanding to technology adoption, Protection Motivation Theory (PMT) implies that the people undertake protective actions in response to the perceived threats (Rogers, 1975). In the same light, the problem of privacy is viewed as a perceived danger within the context of AI-personalization due to concerns about the misuse of data and oversaturation (Martin and Zimmermann, 2024). Additional research was Self-Determination Theory (SDT) of competence, autonomy, and relatedness, which has been viewed as one of the psychological needs of the users (Deci and Ryan, 1985). As one of the variables in the study, the perceived AI competence according to SDT is presented because of the nature of its effectiveness and capability when using AI personalization (McKee *et al.,* 2023). Moreover, this feeling of competence makes the employees more engaged since motivated and competent employees are more engaged in terms of emotion and cognition (Kaur and Mittal, 2020; Singh *et al.,* 2024). Greater engagement, in its turn, leads to greater employee retention, as employees who are engaged will tend to remain more committed to the organization in the long term (Saks, 2022). Primarily, the theories are complementary to one another, as opposed to redundant, whereas UTAUT 2 describes the fact that the employees will accept and believe in the AI personalization tools; nevertheless, it does not answer how the privacy threats can impact the latter (which is the role of PMT) or how intrinsic motivation can be maintained (which is the role of SDT). PMT would only highlight defensive risk appraisals without defining technology acceptance and motivation, and SDT would only fail to mention the importance of privacy concerns and adoption mechanism. The present study is a more comprehensive journey towards sustained retention (SDT) by integrating them, starting with the adoption (UTAUT2) and the next stage of risk appraisal (PMT) and finally. This offers a detailed description of AI personalization in remote work at a multilevel than would have been provided by a single framework.

2.3. Hypothesis Development

In this section, all the variables with hypotheses are discussed in detail. Table 1 presents the key variables used in this study, along with their operational definitions and sources, to ensure theoretical clarity and reliability throughout the study, and Figure 1 shows the research framework outlining the hypothesized relationship of variables in the study.

2.3.1. AI-Driven Personalization (AIP)

AIP is the customization of technological work experiences based on user data, behavioral patterns, and preferences. It includes job assistance or resource provision to enhance job satisfaction and employee retention (Teepapal, 2025). It is downstream of psychological and behavioral outcomes because AIP enhances personal autonomy and competence (SDT) by providing customized interaction as per need (Yang *et al.,* 2025). Sodiya *et al.* 2024 stated that AIP influences performance expectancy (UTAUT2) as it is established through adaptive interfaces,

customized feedback, task recommendations, and emotional tone detection, offering personalized sustenance. However, Chandra *et al.* (2022) argued that personalization in consumer contexts is well-explored; its application to internal workforce management, particularly for employee retention in remote work, remains under-researched.

Table 1. Definition of Variables

Variables	Definition	Reference
AIP	"AI personalization refers to AI-driven customization and support of work experiences, such as task assistance or resource provision, to enhance job satisfaction and employee retention."	(Teepapal, 2025; Venkatesh *et al.*, 2012).
ET	"ET is an attitude characterized by a confident belief that AI personalization will operate with integrity without exploiting vulnerabilities."	(Ameen et al.,2022; Kim *et al.*, 2023; Venkatesh *et al.*, 2012)
PAC	"PAC refers to an employee's perception of their ability to use AI personalization tools effectively, ethically, and adaptively in remote work settings."	(Mehrvarz *et al.*, 2021; Hidayat-ur-Rehman, 2024)
EE	"EE refers to an employee's physical, mental, and emotional involvement in their work tasks, including collaboration with others."	(Aulia and Lin, 2025; Kular *et al.*, 2008)
PC	"PC refers to employees' concerns regarding the collection, analysis, and use of private information by AI personalization systems in ways that exceed their original intent or consent."	(Awad and Krishnan, 2006; Bleier and Eisenbeiss, 2015)
ER	"ER refers to how employees perceive the organization's use of AI personalization tools to improve work experiences, enhance satisfaction, and encourage long-term retention in remote work settings."	(Khalid, and Nawab, 2018; Habeck *et al.*, 2010)

Note: AI-Driven Personalization (AIP), Employee Trust in AI (ET), Perceived AI Competence (PAC), Employee Engagement (EE), Privacy Concern (PC), Employee Retention (ER).

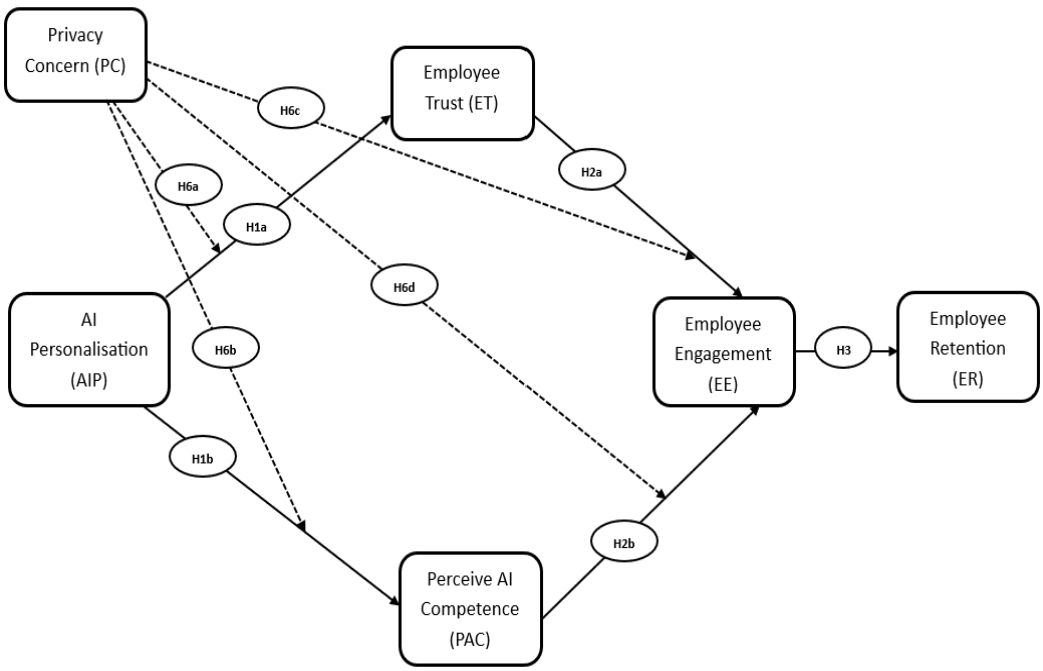

Figure 1. Research Model

Czarnitzki *et al.* (2023) and Murphy (2025) have focused on automation or productivity developments without analyzing the emotional and motivational responses that AIP can trigger in employees. AIP allows user to experience personalized content and suggestions that enhance their engagement and trust in the system.

According to the personalized privacy paradox theory, perceived usefulness and relevance of personalized features influence user interaction capacity, trust, and competence of AI results (Hardcastle *et al.,* 2025; Qin *et al.,* 2024). Therefore, this study addresses this critical gap by aligning AIP as a planned lever for improving employee retention. Further, it proposes the following hypothesis:

- H1a: AIP positively influences ET.
- H1b: AIP positively influences PAC.

2.3.2. Employee Trust in AI (ET)

Trust is believed to be among the first psychological factors in such a process as the adoption of technology (Roberts *et al.*, 2021). The SDT perspective holds that, the need of competence and need of power of trust-satisfied employees. To interact with AI, relatedness leads to intrinsic motivation (UTAUT2) (Sodiya *et al.,* 2024). In remote work, employees and their superiors trust each other because of the absence of direct supervision. managers, as one of the factors affecting job fulfillment and efficiency (Orlandi *et al.,*2024). Similarly, in AI, employee trust indicates the confidence that AI will behave in a competent, reliable and ethical manner. It emphasizes that trust is critical in human or machine analogs, and should be very crucial in the work place. efficiency (Kong *et al.,*2023). ET is an attitude that includes a self-assured perspective that AI. personalization will be conducted with integrity without taking advantage of weaknesses (Ameen *et al.,* 2022; Kim *et al.*, 2023). Wanner *et al.* (2022) and Power *et al.* (2021) stated that the lack of transparency and fear of surveillance might hinder trust in AI-based systems, especially when personalization involves behavioral data. Further prior research suggests that when user feel high engagement and accurate AI recommendations, their overall interaction becomes positive. From the perspective of stimulus-organism-response (SOR) engagement, it acts as a cognitive affective mechanism transforming personalization into experiential satisfaction (Foroudi *et al.,* 2025; Marvi *et al.,* 2025). Therefore, the current study posits the following hypothesis that employee trust acts as a mediating mechanism between AI personalization and employee retention, allowing smoother acceptance and more positive work experiences:

- H2a: ET positively influences EE.
- H4a: ET mediates the relationship between AIP and EE

2.3.3. Perceived AI Competence (PAC)

Perceived control refers to the extent to which employees believe that AI tools are precise and capable of supporting work tasks (Gödöllei and Beck, 2023). Mehrvarz *et al.* (2021) and Hidayat-ur-Rehman (2024) refer to PAC as an employee's perception of their ability to use AI personalization tools effectively, ethically, and adaptively in remote work settings. In line with UTAUT2 and SDT, higher perceived competence reduces user unwillingness and improves perceived usefulness, thus endorsing continued usage and trust. However, Chiu *et al.* (2021) and Tiwari *et al.* (2024) stated that it has often been overlooked how employees cognitively appraise the "intelligence" of AI systems in terms of decision quality, especially in remote work contexts where AI may provide suggestions, alerts, or feedback autonomously. This gap prompts the analysis of perceived AI competence as major explanatory. Variable that was used to relate AI personalization and organizational performance such as retention. Therefore, the hypothesis presented by the study is as follows:

- H2b: PAC positively influences EE
- H4b: PAC mediates the relationship between AIP and EE

2.3.4. Employee Engagement (EE)

EE, which is the level of psychological occurrence and dedication to work is a good indicator of retention (Kaur and Mittal, 2020; Rajak *et al.,* 2023). EE refers to a physical, intellectual, and emotional attachment of an

employee to work activity, and collaboration with other people (Aulia and Lin, 2025; Kular *et al.,* 2008). In line with SDT, AI It is possible to increase the engagement through personalization that allows autonomy, competence, and connection. Along with the essence needs of others. Nevertheless, current research has started.

To empirically investigate the possibility of personalized AI tools to increase employee engagement in. distant environments, especially those where a human is restricted in his/her interaction (Liang *et al.,* 2022; Will Arachchige *et al.,* 2024). The current study integrates this underexplored mediating pathway, bridging personalization design with engagement to examine its impact on long-term commitment and provides the following hypothesis:

- H3: EE Positively Influences ER
- H5: EE mediates the relationship between AIP and ER.

2.3.5. Privacy Concern (PC)

PC is how employees feel uneasy about how AI systems collect, save, and use their personal and behavioral data (Martin and Zimmermann, 2024). Data tracking may feel intrusive in highly personalized environments and trigger resistance even if personalization advances performance (McKee *et al.*, 2023). PC functions as a boundary condition, moderating the effect of AIP on engagement and psychological mechanisms. According to PMT, such intrusiveness is perceived as a threat, prompting users to assess the risk and coping ability (Hassandoust and Techatassanasoontorn, 2020). PC is when users feel in control of their data (low PC); they are more likely to respond adaptively and accept personalization. When PC is high, defensive and skeptical reactions like distrust or avoidance have been seen (Prince, 2018). Moreover, Bandara *et al.* (2020) and Kim *et al.* (2023) discussed PC more in consumer data contexts; however, limited research addresses how such concerns affect internal AI adoption and its relational outcomes, like trust control and engagement in the workplace. Illustration from the Privacy Calculus Theory (PCT) and Reactance Theory (RT), it is proposed that PC moderates the strength of direct and indirect relationships in the model. It can be seen that when PC is high, the engagement and effectiveness strategies (such as AIP, ET, and PAC) outcomes decreased because of skepticism and resistance (Zhu *et al.,* 2024). On the other hand, when PC is lower, it may provide more actual info exchange and robust relation results, influencing the indirect effect by trust and other mediators (McKee *et al.,* 2023).

- H6a: The relation between AIP and ET is moderated by PC
- H6b: The relationship between AIP and PAC is moderated by PC.
- H6c: The relationship between ET and EE is moderated by PC
- H6d: The relationship between PAC and EE is moderated by PC.
- H7a: PC moderates the indirect effect of AIP on EE through ET and PAC.
- H7b: PC moderates the indirect effect of AIP on ER through ET, PAC, and EE.

2.3.6. Employee Retention (ER)

In the HR context, retention is considered a critical outcome, particularly in information-intensive segments like information technology (Kossyva *et al.,* 2021). ER refers to an organization's ability to keep its employees over time (Kamselem *et al.,* 2022). For keeping employees' intention to stay, AI-personalization can shape a more engaging and helpful remote work environment (Aulia and Lin, 2025). According to SDT, it suggests that when psychological needs are met through trust, competence, and engagement, then motivation increases. It is very significant to understand how employees perceive the organization's use of AI personalization tools to advance satisfaction, as work experience leads to higher retention in remote work (Khalid and Nawab, 2018; Habeck *et al.,* 2010). Considering AI personalization's direct and indirect influence on retention through psychological and contextual mechanisms, this study addresses this theoretical and empirical gap. In relation to direct and moderate relationships, the study provides sequential mediation of AIP on ER by ET, PAC, and EE, which shows an indirect and moderate path.

- H8: The effect of AIP on ER is mediated by ET, PAC, and EE.

3. Research Method

3.1. Data Sampling and Collection

An online survey was used to test the hypotheses by using Google Forms between March. 2025 and May 2025. The research was conducted in strict compliance with the ethical standards of research, including anonymizing the responses of the participants, safe storage of data and informed consent to safeguard the privacy and confidentiality of all the respondents. Here the survey started with the collection. Demographic (gender, age, work setup). Following the error cleaning process, only 322 valid replies were left out of the initial 463 replies. 138 were eliminated due to poor-quality responses. Out of the respondents, 67.4 percent were male and. Female, 32.6% and none of them chose not to provide this information. The majority of the age range of 25-35 age bracket had the greatest number of participants (54.3), then 26.1% aged 36-45. Years 14% of 46-55 years and 5.6% of 56-65 years. This age demographic indicates a very young population of employees who may be technologically savvy and are well versed with AI. Applications.

With regards to work models, a great percentage (78.9) of the respondents worked remotely, the rest 21.1% worked in office-based jobs. This is a consistent distribution. And the focus of the study on a remote working setting.

Table 2. Gender, Age Group, and Working Model Ratio

Demographic characteristics		No.	Percentage
Gender	Male	217	67.40
	Female	105	32.60
Age	25-35 years old	175	54.34
	36-45 years old	84	26.1
	46-55 years old	45	13.97
	56-65 years old	18	5.59
Working Model	Remote Work	254	78.88
	Office-based Work	68	21.12

In the study, snowball sampling method was used and this became effective in achieving its purpose. employees of Indian organizations, most of whom are at home. Given the scatteredness of geographically distant workforce and the inability to reach such a population directly,The snowball sampling was used to enable the participants to make referrals to peers and colleagues and broaden the sample. In a specific and effective way. This strategy made sure that the data captured views of those who have been directly exposed to the concept of AI-based personalization at the workplace due to remote working.

3.2. Measures

The study includes various constructs and their variables, as detailed in Table 3. All items' measures used a 1 to 5 Likert scale, where strong disagreement refers to 1, and strong agreement refers to 5.

Table 3. Measurement items

Variables	Items	References
AIP	AI personalization in my remote work AP1 is actively powered by AI technologies. AP2- customizes my tasks to match my needs or preferences. AP3- provides helpful support for completing tasks or learning new skills. AP4- makes my job more satisfying. AP5- increases my desire to stay in this job.	(Teepapal, 2025; Venkatesh *et al.,* 2012).

ET	ET1- AI personalization in my remote work works effectively and gives me confidence. ET2-AI personalization in my remote work does not exploit my personal or professional vulnerabilities. ET3-I trust the personalized recommendations and insights provided by AI in my remote work. ET4-AI personalization in my remote work acts with integrity.	(Ameen *et al.*,2022; Kim *et al.*, 2023; Venkatesh *et al.*, 2012)
PAC	To improve my workflow in remote work settings, PAC1-I feel capable of using AI personalization tools. PAC2-I use AI personalization tools effectively. PAC3-I use AI personalization tools ethically. PAC4-I adapt to updates in AI personalization tools and integrate them into my work.	(Mehrvarz *et al.*, 2021; Hidayat-ur-Rehman, 2024)
EE	AI Personalization in my remote work EE1 helps me stay physically engaged with work processes (e.g., meetings, coordination). EE2 Helps me feel emotionally connected to my work. EE3 Improves my mental focus, such as creativity and problem solving. EE4 Improves collaboration with my team.	(Aulia and Lin, 2025; Kular *et al.*, 2008)
PC	I am concerned that AI personalization tools PC1 Collects more information about me than necessary. PC2 May analyse my personal or professional data without my consent. PC3-May use data in ways I did not initially agree to or expect. PC4 May misuse my data.	(Awad and Krishnan, 2006; Bleier and Eisenbeiss, 2015)
ER	ER1-I see long-term career benefits in continuing to work in this AI-personalized remote work environment. ER2-I see my long-term career growth as aligned with this AI-driven remote work model. ER3-I would recommend this organization because of its AI-enhanced remote work experience. ER4-This organization offers a remote work setup that fits me well due to its AI personalization.	(Khalid and Nawab, 2018; Habeck *et al.*, 2010)

Note: AI-Driven Personalization (AIP), Employee Trust in AI (ET), Perceived AI Competence (PAC), Employee Engagement (EE), Privacy Concern (PC), Employee Retention (ER).

3.3. Analysis of Data

In the present research, the SmartPLS 4 software was utilized to test the research hypotheses. Partial Least Squares Structural Equation Modeling (PLS-SEM) is an empirical method (Singh *et al.*,). 2025). This approach was deemed so due to its strong visualization tool, intuitive. interface, and ability to handle complicated structural models (Akter *et al.*, 2017; Fornell and Larcker, 1981; Gefen *et al.*, 2011). In PLS SEM a dual phase process mostly involves testing measurement model in order to establish its reliability and validity. Subsequently, in the second stage, a bootstrapping technique was utilized to determine the analysis of the structural model. the statistical significance of the assumed relationships (Hair *et al.*, 2017; Hair *et al.*, 2021).

4. Result

SEM PLS had been done following Common Method Variance (CMV) to validate the validity of. The results. As the results could show, CMV is not a critical problem, as the dominant factor. Explained 17.20% of the total variance, which is less than half of the threshold (Kock, 2015; Podsakoff *et al.*, 2003). Besides, to test the variance

inflation factors (VIF) of constructs, the overall collinear test led to a threshold of 3.3 (Hair *et al.,* 2017; Kock and Lynn, 2012). Based on the findings, the VIF of all the constructs was between 1.0 and 2.4 implying. There are no significant issues of collinearity; hence, CMV is not a significant problem in the study.

4.1. Reliability and Validity

For reliability and validity evaluation, a measurement model analysis has been done, including discriminant validity, convergent validity, and overall reliability. The AVG value exceeds 0.50, showing all constructs strong convergent validity. This directs that all the items of each construct be measured precisely (Hair *et al.,* 2017). However, the items AIP2, PC2, and EE2 have been removed in the initial run due to their low loading score. Furthermore, for assessing the consistency of measurement, we used composite reliability (rho_c). The composite reliability scores above 0.70 are considered reliable (Hair *et al.,* 2017). The study reports rho_c and average variance extracted (AVE) to evaluate internal consistency and convergent validity, which is widely accepted in SEM-PLS literature more vigorously than Cronbach's alpha or rho_A for reflective measurement models (Hair *et al.,* 2017; Hair *et al.*,2021). All the scores cross the 0.70 threshold, confirming the reliability and validity of the measurement model mentioned below in Table 4.

Table 4. Measurement Model Result

Constructs	Items	Loading Factor	VIF	AVE	Composite reliability (rho_c)
AIP	AIP 1	0.752	1.070	0.627	0.770
	AIP 3	0.830	1.070		
EE	EE 1	0.752	1.049	0.607	0.756
	EE 3	0.806	1.049		
PAC	PAC1	0.794	1.975	0.620	0.867
	PAC2	0.786	1.687		
	PAC3	0.751	1.761		
	PAC4	0.817	1.980		
ET	ET 1	0.782	2.141	0.580	0.847
	ET 2	0.761	1.605		
	ET 3	0.760	2.002		
	ET 4	0.743	1.740		
PC	PC 1	0.904	1.697	0.661	0.853
	PC 3	0.820	1.553		
	PC 4	0.703	1.388		
ER	ER 1	0.798	1.944	0.632	0.873
	ER 2	0.806	1.559		
	ER 3	0.770	1.803		
	ER 4	0.805	1.774		

Note: AI-Driven Personalization (AIP), Employee Trust in AI (ET), Perceived AI Competence (PAC), Employee Engagement (EE), Privacy Concern (PC), Employee Retention (ER).

The discriminant validity is examined by the HTMT and the Fornell-Larcker criterion. According to Hair *et al.* (2017), HTMT score must be below 0.90 for establishing discriminant validity. In the current study, all HTMT below 0.90 are presented in Table 5. Also, Table 6 mentions the values of Fornell-Larcker. If the square root of the AVE for each variable exceeds its correlation with other variables in the model, then discriminant validity is confirmed. These evaluations collectively demonstrate that the measurement models possess discriminant and convergent validity. Figure 2 presents a structural model where path coefficients were used to demonstrate the hypothesized relationships among research constructs.

Table 5. Heterotrait-Monotrait Ratio (HTMT) Results.

	AIP	EE	ER	ET	PAC	PC	PC x ET	PC x PAC	PC x AIP
AIP									
EE	0.801								
ER	0.251	0.498							
ET	0.446	0.517	0.301						
PAC	0.544	0.328	0.138	0.116					
PC	0.169	0.379	0.183	0.222	0.072				
PC x ET	0.253	0.447	0.216	0.446	0.212	0.061			
PC x PAC	0.250	0.284	0.174	0.195	0.053	0.035	0.291		
PC x AIP	0.252	0.450	0.072	0.165	0.163	0.130	0.409	0.431	

Note: AI-Driven Personalization (AIP), Employee Trust in AI (ET), Perceived AI Competence (PAC), Employee Engagement (EE), and Privacy Concern (PC), Employee Retention (ER).

Table 6. Fornell-Larcker results

	AIP	EE	ER	ET	PAC	PC
AIP	0.792					
EE	0.306	0.779				
ER	0.139	0.276	0.795			
ET	0.251	0.278	0.239	0.762		
PAC	0.316	0.175	0.116	0.095	0.787	
PC	0.077	0.208	0.154	0.186	0.026	0.813

Note: AI-Driven Personalization (AIP), Employee Trust in AI (ET), Perceived AI Competence (PAC), Employee Engagement (EE), and Privacy Concern (PC), Employee Retention (ER).

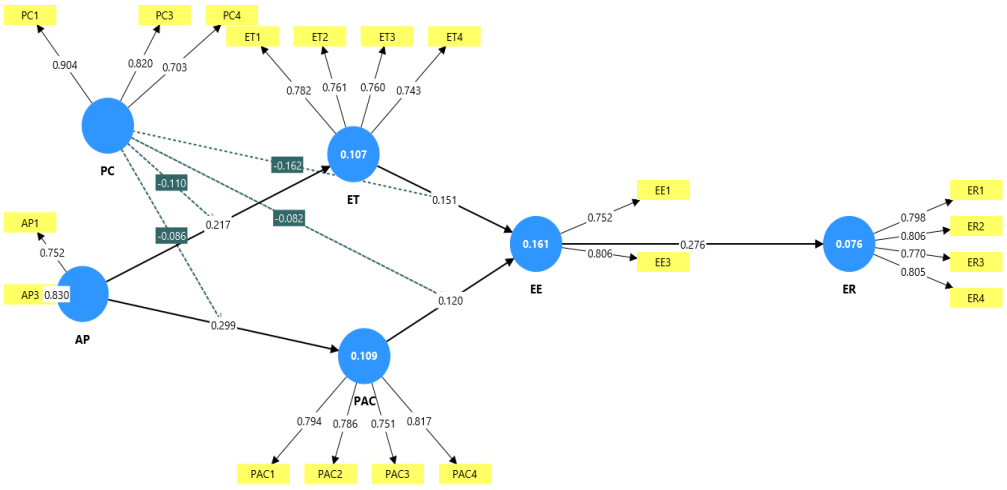

Figure 2. PLS-Structural Path

4.2. Hypothesis Testing

In this study, we used 5000 one-tailed subsamples with a 5% significance level for bootstrapping. According to Hair *et al.* (2017) and Hair *et al.* (2021), hypotheses with a p-value less than 0.05 are supported. The results, in Table 7, provide several key findings. In H1a (AIP -> ET) and H1b (AIP -> PAC), support is provided as (β = 0.217, p = 0.00), (β = 0.299, p = 0.00), respectively, indicating a significant positive relationship. Moving further with our mediator's direct relationship H2a (ET -> EE), H2b (PAC -> EE), H3 (EE -> ER) is also supported as (β = 0.151, p = 0.002) (β = 0.120, p = 0.027) (β = 0.276, p = 0.00), presenting a positive significant relationship. PC is the moderator having a direct and moderating relationship with other variables. Moving further to moderating relationship H6a (PC x AIP -> ET) is supported as (β = -0.110, p = 0.003), showing a moderating relationship. In H6b (PC x AIP -> PAC) is rejected as (β = -0.086, p = 0.066), not moderating. In H7a (PC x ET -> EE) is supported (β = -0.162, p = 0.027) as moderating. Though in H7b (PC x PAC -> EE) is rejected (β = -0.082, p = 0.130) as not moderating.

Table 7. Direct Effect Result

Hypothesis	Path	β	SD	T statistics	P values	Result
H1a	AIP -> ET	0.217	0.055	3.918	0.000	Supported
H1b	AIP -> PAC	0.299	0.054	5.537	0.000	Supported
H2a	ET -> EE	0.151	0.053	2.871	0.002	Supported
H2b	PAC -> EE	0.120	0.062	1.931	0.027	Supported
H3	EE -> ER	0.276	0.054	5.141	0.000	Supported
H6a	PC x AIP -> ET	-0.110	0.041	2.697	0.003	Supported
H6b	PC x AIP -> PAC	-0.086	0.057	1.507	0.066	Rejected
H6c	PC x ET -> EE	-0.162	0.084	1.926	0.027	Supported
H6d	PC x PAC -> EE	-0.082	0.073	1.127	0.130	Rejected

Further study examines the mediating role of ET, PAC, and EE in the relationship between AP and ER. As shown in Table 8, the indirect effect indicates that H4a-b (AIP -> EE) and H5 (AIP -> ER) supported (β = 0.069, p = 0.005); (β = 0.019, p = 0.021), have an indirect effect. In H4a-b, the total indirect effect of AIP on EE through ET and PAC, conceptually, both ET and PAC act as mechanisms through which personalized AI interventions translate into higher engagement, highlighting the importance of building trust and competence in an AI-mediated remote work environment. In H7a (PC x AIP -> EE) is significant as (β = -0.027, p = 0.025); while H7b (PC x AP -> ER) is not supported as (β = -0.007, p = 0.055), with no indirect effect.

Table 8. Indirect Effect Result

Hypothesis	Path	B	SD	T statistics	P values	Result
H4a-b	AIP -> EE via ET and PAC	0.069	0.026	2.603	0.005	Supported
H5	AIP -> ER	0.019	0.009	2.026	0.021	Supported
H15	ET -> ER	0.042	0.018	2.336	0.010	Supported
H16	PAC -> ER	0.033	0.020	1.692	0.045	Supported
H7a	PC x AIP -> EE	-0.027	0.014	1.957	0.025	Supported
H7b	PC x AIP -> ER	-0.007	0.005	1.601	0.055	Rejected
H21	PC x ET -> ER	-0.045	0.027	1.637	0.051	Rejected
H22	PC x PAC -> ER	-0.023	0.022	1.028	0.152	Rejected

In this study, H8 examines the sequential mediation of AIP on ER through ET, PAC, and EE, moderated by PC. The study tested indirect and moderated paths (ET -> ER) and (PAC -> ER), which is supported as (β = 0.042, p = 0.010); (β = 0.033, p = 0.045) has an indirect effect. Showing that, trust and competence mediate the influence of AIP on ER, However H21 (PC x ET -> ER), and H22 (PC x PAC -> ER), is not supported as (β = -0.007, p = 0.055); (β = -0.045, p = 0.051) no moderating effect suggesting that PC does not condition alter this sequential effect. Therefore, this is all combined in H8 to avoid complications and keep in logical flow; overall, H8 is partially supported.

5. Discussions and Implications

In this study, a total of 8 hypotheses have been examined to understand AI personalization in remote work, focusing on trust, control, engagement, and retention of employees, considering their privacy as significant. According to the findings, H1a and H1b suggest that AIP positively influences ET and PAC, respectively, which is also supported by our results. This suggests that when AI tools are personalized for individual employee needs and preferences, they not only build a sense of trust in the technology but also enhance the perception that employees retain meaningful control over their work processes (Chuang *et al.,* 2025). These are similar to existing research that underlines personalization as a key factor of trust in AI systems, mostly when personalization is transparent and perceived as beneficial (Amil, 2024; Mehrvarz *et al.,* 2021). These finding shows that AIP intervention enhances trust in AI, consistent with SDT, where competence supports engagement, and in UTAUT2, where performance expectancy is connected with the attitude of individuals. Also, studies have shown that the perception of control is bound when employees comprehend how AI makes decisions and feel they can influence or control those decisions when required (Teepapal, 2025; Xu *et al.*,2024).

H2a results show that ET positively influences EE, backing the proposed hypothesis. This hypothesizes that in case employees have confidence in the AI deployed in their workplaces and feel that it is trusted, hypocritical, and facilitative, then they are likely to be committed to their roles (Aulia and Lin, 2025; Wanner *et al.,* 2022). Trust brings psychological safety because it reducing indecency and that gives the employees a go-ahead and makes them make tough decisions. Such results are well consistent with the existing literature that points to the fact that trust in technology. Empowers the employees to believe that they can manage results (Ameen *et al.,* 2022; Zhang *et al.,* 2023). The outcomes of H2b reveal that EE is positively affected by PAC. Proposed hypothesis. One of the elements of psychological possession is the employee engagement. And confidence is boosted by the perceived technology control (Mehrvarz *et al.*, 2021; Hidayat-ur-Rehman, 2024). This finding is comparable to the previous studies that point out that autonomy in collaboration with technology offers greater interest and self-efficacy (Shahzad *et al.,* 2023). In short, Trust reduces hesitation and builds confidence, allowing employees to take the initiative. This effect extends SDT by showing how competence and trust jointly foster engagement in an AI-mediated work environment. Further, H3 results indicate that EE positively influences ER, also affirming the proposed hypothesis. According to findings, when employees feel vested in their jobs, they tend to exhibit a willingness to embrace change and accept new technologies. Involved employees are likely to show higher motivation, flexibility, and openness to innovation (Liang *et al.,* 2022; Will Arachchige *et al.,* 2024). Prior literature indicating the same as psychological enabling is a primary predictor of willingness for organizational change. Also, it highlights engagement as a key predictor of retention in remote work or digitally mediated work environments, in non-Western contexts like the Indian tech sector. In such cases, hierarchical organizational structure, cultural norms, and different levels of technological maturity influence how employees perceive AI, trust, and control (Kaur and Mittal, 2020; Makridis and Han, 2021).

The moderating analysis received mixed results across the four hypothesized interactions. For The interaction, term PC and AIP H6a plays an important role in ET implying that as the level of privacy is high, the impact of AI personalization on trust is more beneficial. It means that personalization can serve as a trust buffer even in privacy-sensitive. Conditions, which substantiate the previous research (Martin and Zimmermann, 2024). However, H6b PC and AIP influence PAC was not supported significantly, which represents privacy. Concerns do not materially change the effect of AI personalization on PAC, which could be due to the fact that control insights are more system-based than privacy attitudes, which also coincide. Along with an analysis of the previous studies (Campbell *et al.,* 2025; Kronemann *et al.,* 2023).

Regarding empowerment outcomes, H6c PC and ET have a significant influence on EE, which was supported, confirming that the effect of ET on EE is amplified when privacy concerns are high. This highlights the strengthening role of trust in engaging employees, particularly in contexts where data sensitivity is a concern (Aulia and Lin, 2025). Conversely, H6d PC and PAC had a significant influence on EE, which was rejected, suggesting that privacy concerns do not significantly influence the relationship between PAC and EE. As per Kim *et al,* (2023) align with our results suggesting it as may consider that once control is established; privacy concern does not further condition its empowerment effect.

In H4a-b EE and H5 ER, AIP has a positive effect on directing employees to be more involved when they feel encouraged by AI. In H4a-b, it can be seen that AIP enhances engagement by building trust and strengthening

employees' perception of competence. When employees trust AI, they feel more capable in interacting, resulting in engagement. This explicitly illustrates performance expectancy from UTAUT2. In H5, highlights tangible behavior outcomes connecting PMT and SDT to practical HR outcomes like engagement and trust. Further, in H7a-b, moderating effects suggest that PC is moderating and decreasing the positive effect of AIP and ET on engagement when concerns are considerable. Lastly, the H8 study incorporated sequential mediation of AIP on ER by ET, PAC, and EE, which indicates a significant indirect effect and a non-significant moderating effect. This finding aligns with prior research that AIP has a positive effect on EE, which is robust when employee shows capability and trust in the system, even in terms of privacy concerns (Aulia and Lin, 2025).

5.1 Theoretical Contribution

The current study provides insights into organizational behavior and AI adoption in many ways. By extending PMT, it suggests that showing privacy functions as a perceived threat moderates the trust-enhancing capacity of AI-personalization in remote work. Further, it advances by relating the level of trust of employees to AI with the results of engagement and retention, therefore. Expanding the area of technology acceptance research to the area of organizational sustainability. Moreover, it invests in SDT by showing that AI-based personalization might promote perceived. Only with protection of privacy, competence and engagement. Together, these insights provide a multi-layer insight into the impact of personalization technologies on employees within a workforce setting, and, at that, before the previous consumer-oriented and well-being-oriented research (Afroogh *et al.,* 2024; Martin and Zimmermann, 2024).

5.2 Practical Implication

Regarding management perspective, the results indicate that Multinational corporations (MNCs) must not perceive AI personalization as technological efficiency tool, but as a strategic one. Lever for talent retention. Especially in remote working, where turnover is, employee turnover is reduced. Personalization can be disrupted, AI-based to improve the engagement, and competence can be supported. Nevertheless, personalization cannot succeed without stringent privacy protection, which would destroy trust. The effective types of AIP are personalized task recommendation, adaptive training modules. And individual feedback, which is capable of improving competency and involvement. It is important to enact data policies, periodic auditing and resolve employee consent procedures to balance. Customized perks and savings and retention. MNCs must aim at controlling a culturally. Varying workforce in an evolving regulatory landscape (e.g. GDPR in Europe and others). Flexible regulatory policies in Asia). Therefore, companies that seek AI personalization. Should embrace flexible privacy control system to guarantee credibility and retention across. Thus, organizations that want to increase AI personalization are forced to consider models to maintain trust and retention.

6. Conclusion

In the present study, the researcher aims the attention on the AIP and ER in the case of remote work. The study offers a hybrid model of PMT, UTAUT2, and SDT. The reaction is implied in the findings. To RQ2 in that PC directly affects engagement, and it is extremely complicated as compared to its moderating effect. Remote work becomes more entrenched in the organizational culture, as it is getting faster. This is necessary to maintain a loyal flexible work force. Despite this, the cross-cultural issue is pertinent regardless of the fact that the Indian IT sector provides a fertile environment to study AI. Applicability of this result to the general population might be restricted. Cultural Differences, Organizational. Structures and regulations of data privacy in different countries may affect the perception of employees. Of credibility, ability, and participation. The relationship in future literature needs to be investigated. Different international environments to check the soundness of the suggested mechanism and improve the. Universality of AIP strategies in HR. The snowball sampling is employed in the study and it lacks representativeness, and creates a possible selection bias. Future studies can use probability-based or stratified sampling to enhance external validity. PC is assumed as a mere moderator in the study to preserve the clarity of theoretical and speculative effect, but in others (industry, regions, etc.) PC may have a direct implication on trust, engagement, and competence. These direct effects can be investigated in future research using justifiable theories.

This paper is about the issues of trust and privacy and presents a premise on how to engage and retain employees by adopting AI in remote working. Responsible and effective use of AI technologies can be guaranteed in the future researches.

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Suman Kumar: Conceptualization, Methodology, Investigation, Formal analysis, Writing - Original Draft. Massoud Moslehpour: Validation, Writing - Review & Editing. Ankita Manohar Walawalkar: Writing - Review & Editing. Priyanka Verma: Writing - Review & Editing, Supervision. Kuei-Kuei Lai: Writing - Review & Editing. All the authors read and approved the final version of this manuscript.

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Conflict of Interest

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