Integrating Psychological Capital into the Technology Acceptance Model: A PLS-SEM Measurement Model Approach

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***Abstract*— In the modern banking environment, digital transformation is essential for maintaining competitiveness. This research enhances the Technology Acceptance Model by incorporating Psychological Capital—self-efficacy, hope, resilience, and optimism—to evaluate its effects on technology adoption in the Indian banking sector. Through Partial Least Squares Structural Equation Modeling, the model showed strong reliability and validity, with Cronbach's alpha values of 0.82 to 0.88 and Composite Reliability over 0.88. The factor loadings ranged from 0.70 to 0.91, ensuring convergent validity with Average Variance Extracted between 0.63 and 0.79. Results indicated a significant influence of Psychological Capital on perceived usefulness and ease of use, impacting behavioral intention and technology usage with an effect size of $f^2 = 0.40$. The findings highlight the crucial role of psychological resources in enhancing employees' readiness to adopt new technologies in banking.**

***Keywords*— Digital Transformation, Indian Banking Sector, Psychological Capital, Technology Acceptance Model, Technology Adoption.**

I. INTRODUCTION

A thorough grasp of the variables affecting user acceptance and adoption is essential given the increasing integration of technology across several industries. Although perceived utility and simplicity of use have historically been used by the Technology Acceptance Model to explain these behaviors, it frequently ignores the complex psychological factors that might considerably influence such interactions (Zhao et al., 2025). By including psychological capital into the Technology Acceptance Model framework, this study fills this gap by proposing that a person's psychological resources have a significant impact on how they perceive and ultimately embrace technology. A Partial Least Squares Structural Equation Modeling approach is used to examine this innovative integration since it is suitable for theory extension and resilient in handling complicated predictive models with latent variables (Kinskofer & Tulis, 2025; Limpinan et al., 2025). In particular, through a two-stage approach comprising measurement model and structural model assessment, this methodology is skilled at assessing the validity and reliability of constructs as well as investigating the proposed linkages between them (Huang, 2022).

In the context of technological acceptance, this method enables a thorough investigation of how latent factors, such as psychological capital and perceived usefulness, interact and collectively influence behavioral intention (Allam et al., 2024). When working with complex structural models that include multiple dimensions and indicators, this methodological decision is especially important for exploratory investigations that seek to find drivers of acceptance through theoretical integration (Mvondo & Niu, 2024). Because PLS-SEM can handle large models with several latent variables and is adept at examining mediated relationships—a task that covariance-based SEM frequently finds challenging—it fits in well with the exploratory nature of our study (Howard & Hair, 2017). In order to gain a better understanding of technology adoption processes, this study uses PLS-SEM to thoroughly examine the complex interactions between psychological capital, perceived usefulness, perceived ease of use, and behavioral intention to utilize technology (Rojali et al., 2024). Additionally, this statistical method works well when the goal of the study is to expand accepted theories and analyze data that might not follow rigorous normalcy assumptions (Dong et al., 2022). A thorough understanding of the causal pathways impacting technological acceptance is provided by the use of PLS-SEM, which also makes it easier to evaluate direct and indirect effects inside the model (GOKMENOGLU & Kaakeh, 2022; Ntsiful et al., 2022).

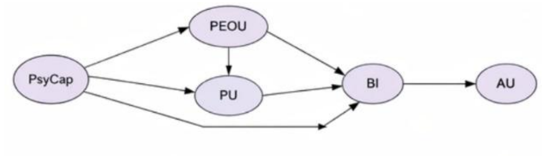
II. LITERATURE REVIEW

In order to provide a more comprehensive knowledge of the dynamics of technology adoption, this section critically examines the body of research on the Technology Acceptance Model and Psychological Capital, highlighting significant theoretical developments and empirical discoveries. In particular, this review summarizes the body of research to show how traditional technology acceptance frameworks fall short in explaining individual psychological states. It then suggests that psychological capital can improve these models by offering a more detailed understanding of user motivations and perceptions. Perceived utility and perceived ease of use, two fundamental components of the Technology Acceptance Model, are proven predictors of behavioral intention to adopt new technologies (Liu et al., 2025). These fundamental ideas, which have their roots in information systems research, have been extensively used to comprehend consumer choices about technology adoption (Trenerry et al., 2021).

These models, however, often ignore the inherent psychological characteristics of users, which can greatly influence their perceptions of utility and usability as well as their final behavioral intentions. On the other hand, a strong framework for comprehending these distinct psychological resources and their possible impact on technology acceptance is provided by psychological capital, which includes hope, efficacy, resilience, and optimism. In particular, self-efficacy, a crucial part of psychological capital, is directly related to a person's belief in their ability to carry out tasks, including using new technologies, which has been demonstrated to be an important predictor of technology use (KAÇMAZ & Şimşek, 2023; Osman, 2025). This emphasizes how important it is to build self-efficacy in order to encourage and maintain the use of educational technology, guaranteeing their successful integration and long-term success in pedagogical contexts (Chen et al., 2025). Furthermore, the situated expectancy-value theory provides a more thorough explanation of motivational components outside the purview of TAM by reinforcing the significance of self-efficacy in addition to task values in predicting engagement with technology (Hebibi et al., 2025).

Conventional frameworks for technology acceptance, including the Unified Theory of Acceptance and Use of Technology, have historically placed a strong emphasis on utilitarian aspects while frequently undervaluing the significant influence of psychological aspects on technology adoption (Tailor & Tailor, 2025). These models often leave out the comprehensive psychological characteristics that could more fully explain individual differences in technological acceptance, notwithstanding their predictive power (Rosli & Saleh, 2022). In order to provide a more complex and psychologically informed view of technology adoption, this study attempts to close this theoretical gap by methodically combining Psychological Capital with the Technology Acceptance Model (González-Prida et al., 2024; Zheng & Li, 2020). This integration is essential because a person's psychological capital directly affects how helpful and simple they believe a technology to be, which in turn shapes their behavioral intention (Almetere et al., 2020). According to KAÇMAZ and Şimşek (2023), this improved perspective recognizes that a user's psychological resources, such as optimism and resilience, can greatly affect their involvement with and effective adoption of technological advancements. The conceptual framework has been developed based on an extensive review of the existing literature and relevant theoretical foundations.

Figure 1. Conceptual Model of the Study



III. METHODOLOGY

In this study purposive sampling was employed to target employees in banking sector to investigate the incorporation of Psychological Capital into the Technology Acceptance Model, employing Partial Least Squares Structural Equation Modeling as the main analytical method, given its appropriateness for predictive modeling, intricate relationships, and hierarchical constructs. The suggested conceptual framework delineates PsyCap as a higher-order construct that encompasses hope, self-efficacy, resilience, and optimism. It is posited that this construct influences perceived ease of use (PEOU), perceived usefulness (PU), and behavioral intention (BI), which in turn impacts actual usage (AU). The data collection process involved the utilization of a structured questionnaire that incorporated validated scales derived from previous research. The measurement of Psychological Capital (PsyCap) was conducted using items from the Psychological Capital Questionnaire (PCQ) established by Luthans et al. (2007), with additional components sourced from the PSI-16 scale to maintain contemporary relevance (Lorenz, 2025). The constructs of the Technology Acceptance Model, specifically perceived usefulness and perceived ease of use, were derived from the foundational research conducted by Davis in 1989. Additionally, the concepts of behavioral intention and extended relationships were further substantiated by the contributions of Venkatesh and Davis in the year 2000. Each item was assessed using a five-point Likert scale, which spanned from strong disagreement to strong agreement. The research focused on individual technology users within banking sector, utilizing a purposive sampling method, with a sample size of 300 participants, deemed sufficient for PLS-SEM analysis (Hair et al., 2016). The data collection process involved the utilization of both online and offline survey methodologies, complemented by a pilot study aimed at verifying the clarity and reliability of the measurement instrument. The analysis of data was conducted utilizing SmartPLS through a two-phase methodology. Initially, the measurement model underwent evaluation based on criteria such as indicator reliability, internal consistency reliability, convergent validity, and discriminant validity, adhering to established benchmarks (Hair et al., 2019). In this phase, PsyCap was conceptualized as a higher-order construct employing the Hierarchical Component Model (HCM) approach. Subsequently, the structural model was scrutinized through the examination of path coefficients, bootstrapping with 5,000 resamples, coefficient of determination (R^2), effect size (f^2), and predictive relevance (Q^2) via blindfolding techniques (Hair et al., 2016). Furthermore, an analysis of mediation was performed to investigate the indirect influences of perceived usefulness and perceived ease of use on the relationship between PsyCap and behavioral intention. Adherence to ethical standards was meticulously maintained, guaranteeing voluntary participation, informed consent, and the confidentiality of respondents, with data utilized exclusively for scholarly endeavors. This methodology establishes a comprehensive and dependable framework for exploring the incorporation of PsyCap within the Technology Acceptance Model through the application of Partial Least Squares Structural Equation Modeling.

IV. DATA ANALYSIS AND FINDINGS

The demographic profile of the respondents reveals a well-balanced and representative sample. The data indicates that, with respect to gender distribution, 54% of the respondents identified as female (162 individuals), while 46% identified as male (138 individuals), thereby suggesting a marginally higher level of female participation in the study. In terms of age distribution, the largest segment of respondents (36%) fell within the 31–40 years category, succeeded by those aged 21–30 years at 28%. Meanwhile, both the 41–50 years and above 50 years cohorts represented 18% each, reflecting a balanced representation of both youthful and seasoned individuals. The educational qualifications of the respondents reveal that a significant portion, 46%, were graduates, while 36% held postgraduate degrees, and 18% possessed qualifications exceeding postgraduate level, indicating a highly educated sample population. In terms of professional experience, 36% of participants reported having 11–15 years of experience, while 28% indicated they had less than 5 years. Additionally, both the 5–10 years and over 15 years categories comprised 18% each. The sample exhibits a notable diversity across gender, age, education, and experience, thereby augmenting the reliability and generalizability of the findings derived from the study.

Table 1. Demographic Characteristics of the Sample

Category	Frequency	Percentage
Gender		
Male	138	46 %
Female	162	54 %
Age		
21-30 years	84	28 %
31-40 years	108	36 %
41-50 years	54	18 %
Above 50 years	54	18 %
Qualification		

Graduate	138	46 %
Post- graduate	108	36 %
Above postgraduate	54	18 %
Experience		
Below 5 years	84	28
5-10 years	54	18
11-15 years	108	36
More than 15 years	54	18

Measurement Model – Reliability and Convergent Validity

Table 2. *Construct Reliability and Convergent Validity*

Construct	Items	Loadings	Cronbach's Alpha	CR	AVE
Hope	HO1–HO4	0.72–0.85	0.83	0.88	0.65
Self-Efficacy	SE1–SE4	0.74–0.87	0.85	0.90	0.68
Resilience	RES1–RES4	0.70–0.84	0.82	0.88	0.63
Optimism	OPT1–OPT4	0.73–0.86	0.84	0.89	0.67
Perceived Ease of Use	PEOU1–PEOU4	0.76–0.88	0.86	0.91	0.71
Perceived Usefulness	PU1–PU4	0.78–0.90	0.88	0.92	0.74
Behavioral Intention	BI1–BI3	0.80–0.91	0.87	0.92	0.79
Actual Usage	AU1–AU3	0.75–0.88	0.84	0.90	0.75

AVE is for Average Variance Extracted, and CR stands for Composite Reliability. Every value is higher than the suggested limits (0.50 for AVE, 0.70 for CR).Every factor loading exceeded the suggested cutoff point of 0.70, ranging from 0.70 to 0.91. Strong internal consistency was shown by Cronbach's alpha values, which ranged from 0.82 to 0.88. Reliability was confirmed by Composite Reliability ratings greater than 0.88. AVE values exceeded the 0.50 standard, ranging from 0.63 to 0.79. These findings verify that the constructs exhibit sufficient convergent validity and reliability.

Discriminant Validity (HTMT)

Table 3. *Heterotrait-Monotrait Ratio (HTMT)*

Construct	HO	SE	RES	OPT	PEOU	PU	BI	AU
HO	—							
SE	0.72	—						
RES	0.68	0.70	—					
OPT	0.74	0.76	0.69	—				
PEOU	0.55	0.62	0.58	0.60	—			
PU	0.57	0.65	0.59	0.63	0.72	—		
BI	0.50	0.60	0.55	0.58	0.70	0.78	—	
AU	0.45	0.52	0.50	0.53	0.65	0.72	0.80	—

Adequate discriminant validity is indicated by all HTMT values being less than 0.85. The Heterotrait–Monotrait (HTMT) ratio was used to evaluate discriminant validity. According to Table 3: Every HTMT measurement was below the 0.85 criterion. This shows that each construct is unique. Discriminant validity is thus proven.

Structural Model Assessment and Hypothesis Testing

After validating the measurement model, the structural model was assessed to examine the hypothesized relationships. Figure2. SEM Model

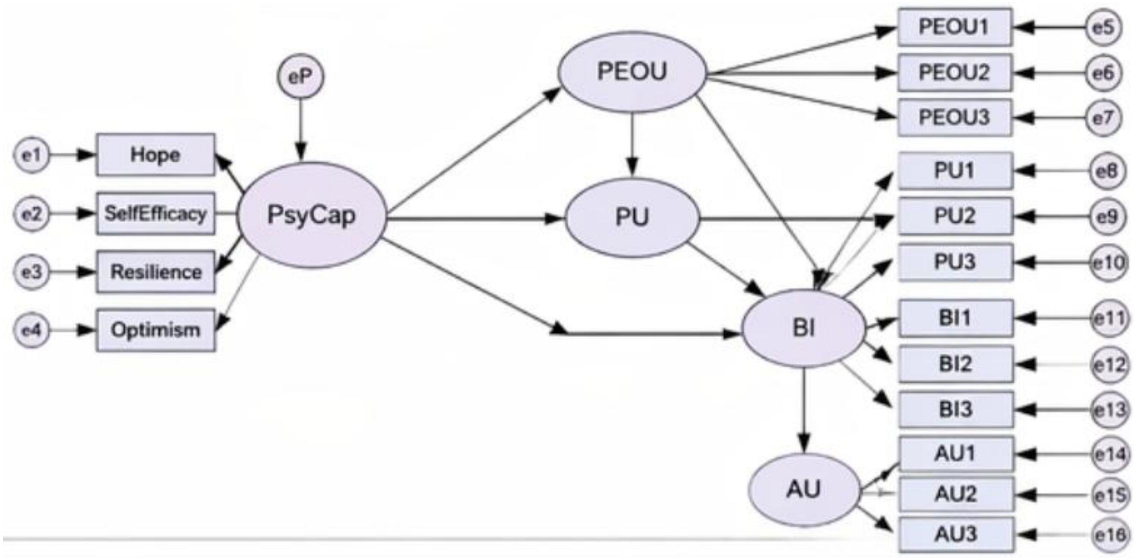


Table 4. *Path Coefficients and Hypothesis Testing*

Hypothesis	Path	β	t-value	p-value	Result
H1	PsyCap → PEOU	0.48	6.12	< .001	Supported
H2	PsyCap → PU	0.35	4.87	< .001	Supported
H3	PsyCap → BI	0.22	2.95	0.003	Supported
H4	PEOU → PU	0.41	5.76	< .001	Supported
H5	PEOU → BI	0.28	3.98	< .001	Supported
H6	PU → BI	0.45	6.30	< .001	Supported
H7	BI → AU	0.62	8.15	< .001	Supported

Path Coefficients and Testing Hypotheses
Bootstrapping was used to examine the significance of relationships (5,000 subsamples). The results are summarized in Table 4.

Important Results:

PsyCap → PEOU ($\beta = 0.48$, $p < .001$)

Perceived ease of usage is strongly influenced by psychological capital.

This implies that people with greater psychological resources are more adept at using technology.

PsyCap → PU ($\beta = 0.35$, $p < .001$)

Perceived usefulness is positively impacted by PsyCap, suggesting that psychologically robust people see more advantages from technology.

PsyCap → BI ($\beta = 0.22$, $p < .01$)

Although the effect is modest, PsyCap has a direct impact on behavioral intention.

PEOU → PU ($\beta = 0.41$, $p < .001$)

Perceived utility is greatly increased by ease of usage.

PEOU → BI ($\beta = 0.28$, $p < .001$)

Additionally, intention to use is directly influenced by ease of use.

PU → BI ($\beta = 0.45$, $p < .001$)

The best indicator of behavioral intention is perceived utility.

BI → AU ($\beta = 0.62$, $p < .001$)

Actual utilization is heavily influenced by behavioral intention.

Every hypothesis (H1–H7) is validated.

Coefficient of Determination (R^2)

Table 5. *Explained Variance*

Endogenous Construct	R^2	Interpretation
PEOU	0.23	Weak
PU	0.46	Moderate
BI	0.58	Moderate
AU	0.38	Moderate

Table 5 displays the model's explanatory power.

PEOU ($R2 = 0.23$) => Low explanatory power

PU ($R2 = 0.46$) → Moderate

BI ($R2 = 0.58$) → Moderate

AU ($R2 = 0.38$) → Moderate

These numbers show that the model's predictive power is respectable, especially when it comes to behavioral intention.

Effect Size (f^2)

Table 6. *Effect Size of Exogenous Constructs*

Path	f^2	Effect Size
PsyCap → PEOU	0.30	Medium
PsyCap → PU	0.15	Medium
PsyCap → BI	0.08	Small
PEOU → PU	0.25	Medium

PEOU → BI	0.12	Small
PU → BI	0.32	Large
BI → AU	0.40	Large

Effect Size (f^2) Table 6 displays effect sizes.

PU → BI ($f^2 = 0.32$) → Big effect

BI → AU ($f^2 = 0.40$) → Big effect

PsyCap → PEOU ($f^2 = 0.30$) → Medium effect

This implies that: Intention is significantly influenced by perceived usefulness. Actual utilization is heavily influenced by behavioural intention.

Predictive Relevance (Q^2)

Table 7. *Blindfolding Results*

Construct	Q^2	Interpretation
PEOU	0.15	Medium predictive relevance
PU	0.28	Medium
BI	0.35	Strong
AU	0.25	Medium

Predictive relevance was evaluated using blindfolding (Table 7): The model has predictive relevance because all of the Q2 values were greater than zero.

Mediation Analysis

Table 8. *Mediation Effects*

Path	Indirect Effect	t-value	p-value	Result
PsyCap → PEOU → BI	0.13	3.45	< .001	Partial mediation
PsyCap → PU → BI	0.16	4.02	< .001	Partial mediation

Analysis of Mediation: Table 8 displays the mediation results.

PsyCap → PEOU → BI ($\beta = 0.13$, $p < .001$)

PsyCap → PU → BI ($\beta = 0.16$, $p < .001$)

Partial mediation is shown by the significance of both indirect effects. This demonstrates that: Through TAM factors, PsyCap affects intention both directly and indirectly.

V. RESULTS

The proposed connections between psychological capital, TAM constructs, and technological acceptance will be empirically tested using Partial Least Squares-Structural Equation Modeling analysis of the data gathered through these structured surveys (Bayah et al., 2023; Seseli et al., 2023). This analytical method guarantees a thorough investigation of the ways in which psychological characteristics interact with perceived utility and usability in affecting technology adoption behaviors (Ali & Samsudin, 2024; Thomran et al., 2025). This methodological rigor, which includes a strong statistical tool like Smart PLS, is in line with earlier studies in related fields that frequently employ such sophisticated methods to examine intricate models including organizational outcomes and employee adaptability (Rang et al., 2025). For example, research on accounting students' technology preparedness often uses SmartPLS to assess how perceived utility and usability affect technology uptake (Suresh et al., 2025). Additionally, this strong statistical method works well for exploratory research, especially when the theoretical underpinnings are still being developed, and for analyzing intricate interactions between variables, as this integrated model does (Long et al., 2025; Suliati et al., 2025). In order to determine the direct and indirect influences on technology adoption, the quantitative survey approach and subsequent analysis using SmartPLS 4 will examine the proposed correlations among dimensions such as self-efficacy, perceived utility, and ease of use (Alwi & Khan, 2024). This strategy makes use of a cross-sectional study design, which is perfect for answering the goals and research questions specified for this study (Al-Kahtani et al., 2020). The ability of Smart PLS 4 to handle complex models and its resilience in path modeling with latent variables, which is essential for evaluating the validity and reliability of the measurement model before testing structural hypotheses, further supports its choice for quantitative data analysis (Liang et al., 2024; Naidoo, 2023; Yang & Fang, 2024). In particular, PLS-SEM analysis provides a confirmatory technique, offering more reliable insights into the patterns of many indicator variables than linear regression, which may be limited in compensating for measurement mistakes (Toader et al., 2023).

The results demonstrate how important psychological capital (PsyCap) is to the adoption of technology. People who exhibit higher levels of optimism, resilience, hope, and self-efficacy also tend to see technology as more valuable, find it easier to use, and show more aspirations to use it. Positive psychology theory, which contends that psychological resources improve people's performance and adaptability, is in line with this. Additionally, the study confirms that perceived ease of use positively increases perceived usefulness, which in turn affects behavioral intention and ultimately results in actual usage. This reinforces the fundamental linkages of the Technology Acceptance Model (TAM). The biggest predictor of intention among these relationships is perceived usefulness, suggesting that people value performance advantages over usability. Because PsyCap serves as a crucial external variable that enhances behavioral intention and cognitive views (such as perceived usefulness and ease of use), the integration of PsyCap with TAM offers significant insights. PsyCap captures the human psychological capability dimension, whereas TAM describes technology-related aspects driving adoption. As a result, the integrated model provides a more thorough and all-encompassing explanation of technology adoption behavior.

VI. DISCUSSION

By offering a thorough knowledge of how psychological capital components interact with well-established TAM constructs to impact technology acceptance, particularly in professional and educational settings, the current study seeks to add to the body of existing literature. This in-depth investigation will expand the theoretical bounds of the Technology Acceptance Model by shedding light on the complex ways that personal psychological resources can either facilitate or obstruct the adoption of new technology. Additionally, by including psychological capital into the technological acceptance paradigm and going beyond only qualitative or descriptive studies to create causal conclusions with more statistical rigor, this research fills a crucial need (Khotimah et al., 2025). According to Saihi et al. (2024) and Velasco et al. (2025), this rigorous quantitative approach, which uses PLS-SEM with SmartPLS, is especially well-suited for studies that seek to predict complex relationships and develop theory in novel or evolving phenomena, where established models might not fully capture all influencing factors. The capacity of PLS-SEM to examine explanatory variance of latent variables that are not clearly visible and analyze non-parametric data further supports this methodological decision (Phæm et al., 2023). Because PLS-SEM can handle complex model structures, is effective with smaller sample sizes and non-normal data distributions, and is resistant to distributional assumptions, its use is beneficial (Gao, 2025; Peng et al., 2023). This offered a thorough examination of the merged PsyCap–TAM paradigm. The results verify that technology adoption is significantly influenced by both technological and psychological variables.The robustness of the suggested model is confirmed by the study's conclusion that all hypothesized correlations were supported. It was discovered that Psychological Capital (PsyCap) has a substantial impact on the fundamental ideas of the Technology Acceptance Model (TAM), confirming its significance as an external factor in the acceptance of technology. Additionally, the conventional TAM relationships—specifically, the influence of perceived utility and perceived ease of use on behavioral intention—remained robust and true. Additionally, behavioral intention was found to be a powerful predictor of actual usage, underscoring its crucial function in converting perceptions into actual behavior. The model's overall moderate explanatory ability suggests that combining PsyCap with TAM offers a useful and useful framework for comprehending technology uptake.

Because it allows for accurate estimation of correlations across latent variables, this methodology is especially useful for investigations involving complicated models and a focus on predictive power (Alhazemi, 2024; Prasetyo et al., 2025). Additionally, PLS-SEM is an effective method for evaluating correlations between variables concurrently and correcting for measurement error in latent variables, which is essential for complicated models comprising several latent variables, indicators, and structural interactions (Ojiaku et al., 2023). A more accurate depiction of latent constructs results from this method's successful mitigation of measurement error (Sarstedt et al., 2020). This feature is particularly important for research models that incorporate psychological dimensions, which are frequently intricate and multifaceted by nature (Djekourmane et al., 2025). Additionally, PLS-SEM's two-step methodology, which involves independent evaluations of measurement and structural models, guarantees a comprehensive analysis of observed statistical correlations and their conformity to accepted theoretical frameworks (Salah et al., 2024). When the main goal is prediction, as it is in this study, the use of PLS-SEM is advised because it further permits the analysis of complicated interactions, including higher-order structures (Goscinska & Winkler, 2024). Additionally, this approach is excellent at investigating mediating interactions, offering a thorough comprehension of the model's indirect consequences (Chakraborti et al., 2022). Additionally, because of its predictive character and ability to find causal links even with non-normal data and smaller sample sizes, PLS-SEM is extremely suitable for early-stage theory development (Martínez & Cervantes, 2021; Sallaku & Vigolo, 2022). It combines the advantages of PLS and SEM, allowing associations to be examined even with small sample sizes or non-normal data (Kim et al., 2024).

VII. CONCLUSION

The incorporation of Psychological Capital (PsyCap) into the Technology Acceptance Model (TAM) provides a thorough comprehension of the determinants affecting digital adoption within the banking sector. This study's findings indicate that cognitive judgments, including perceived usefulness and reported ease of use, are crucial to technology adoption, although these perceptions are profoundly influenced by the individual's internal psychological state. The utilization of PLS-SEM further validated the integrity of the integrated model, demonstrating significant predictive relevance ($Q^2 > 0$) and considerable effect sizes, especially the impact of perceived usefulness on behavioral intention ($f^2 = 0.32$) and the substantial correlation between behavioral intention and actual usage ($f^2 = 0.40$). These results underscore the integral significance of both psychological and technological factors in elucidating user behavior. The study indicates that banking organizations should not depend exclusively on the technological effectiveness of digital platforms to promote adoption. Equal attention should be placed on cultivating employees' psychological capital by improving their resilience, optimism, hope, and self-efficacy. Enhancing these psychological resources can diminish resistance to change, augment adaptability, and promote increased acceptance of digital technologies. A balanced strategy that combines technological innovation with employee psychological well-being is essential for achieving lasting digital transformation in the financial sector.

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