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iTDAF IETI Transactions on Data Analysis and Forecasting

iTDAF | eISSN: 2959-0442 | Vol. 3 No. 1 (2025) | OPEN ACCESS

https://doi.org/10.3991/itdaf.v3i1.52559

PAPER

An Assessment of Organizational Competency, Organizational Readiness and Perceived Usefulness in Light of Behavioral Intention to Use Blockchain Technology

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ABSTRACT

This study examines the connections between organizational competency (OGC), organizational readiness (OGR), perceived usefulness (PU), perceived ease of use (PEOU), and behavioral intention to use (BIU) blockchain technology (BCT), with a specific focus on how technostress (TCS) influences these relationships as a moderator. Using structural equation modelling (SEM) using the SMART PLS 4.0 software, we found that OGC and OGR positively impact PU and PEOU, significantly improving BIU. However, TCS substantially negatively impacts the correlations between PU and BIU, as well as between PEOU and BIU. When TCS (technostress) levels are higher, the positive impact of PU and PEOU on BIU (behavioral intentions to use) decreases. This indicates that higher levels of TCS decrease the perceived advantages of BCT, which subsequently diminishes the desire to use it. These findings highlight the importance of effectively managing TCS to optimize the positive impact that OGC and preparedness have on users' perspectives and intentions. The study underscores the importance of conducting research across multiple cultures in technology acceptance studies and suggests incorporating TCS into future models for more accurate technology adoption outcomes.

KEYWORDS

blockchain technology, organizational competency, organizational readiness, technostress

1 INTRODUCTION

Industry 4.0, a cyber-physical system, emerged as a solution to the challenges faced by industries in the past (Posada et al. 2015) [1]. It was first coined in Germany in 2011 and is a result of the need for an effective digital strategy to address complex problems in manufacturing and production systems (Asgari et al. 2017; Anna Cui

Wang, X., Raza, S. (2025). An Assessment of Organizational Competency, Organizational Readiness and Perceived Usefulness in Light of Behavioral Intention to Use Blockchain Technology. *IETI Transactions on Data Analysis and Forecasting (iTDAF)*, 3(1), pp. 32–48. https://doi.org/10.3991/itdaf.v3i1.52559

Article submitted 2024-09-30. Revision uploaded 2025-01-29. Final acceptance 2025-03-25.

and Gina O'Connor, 2012) [2]. Industry 4.0 consists of key elements such as BCT, nanotechnology, cyber-physical systems, artificial intelligence, robotics, and IoT (Nunes et al., 2022; Purva Grove et al., 2022; Quirin Demlehner et al., 2021a, 2021b; Sonali Vyas and Shaurya Gupta, 2022; Surajit Bag et al., 2021) [3] [4] [5] [6] [7]. Organizations must transform into adaptive ones and embrace digitalization. PwC predicts $900 billion in annual global investments for digitalization starting in 2020 (P. Senna et al., 2023; Georg Reischauer, 2018) [8] [9]. BCT can enhance managerial productivity and facilitate prompt decision-making within organizations (Duan et al. 2019; Tandon et al. 2021; Yogesh Kumar Dwivedi et al. 2019) [10] [11] [12].

Research shows that PU and PEOU positively influence the intention to use new technologies (Tahar et al. 2020) [13]—the more PU, the greater the inclination towards using it. TCS, also known as technology dependence, is an emotive state characterized by an individual's constant reliance on technology and anxiety about the use of technical tools or technology such as blockchain or AI, which can lead to stress and disruption in the work environment as employees in the organization will avoid using technology when they have stress to use it (Belal Panahi, 2023) [14]. Increased reliance on technology has resulted in a rise in techno-stress and work anxiety, both of which may negatively impact job performance and the BIU. Techno-stress can impact organizational responsibilities, PEOU, and usefulness and generate stress. Thus, organizations need to understand how to manage and minimize it. OGC equips employees with necessary skills and knowledge for technology use, positively impacting PEOU and usefulness, ensuring easy use of BCT, ultimately impacting BIU (Yu and Moon, 2021; Long et al., 2013) [15] [16]. Organizational readiness for technology adoption, specifically BCT, is influenced by OGR characteristics, with larger organizations needing more resources, potentially limiting staff's ability to fully utilize AI benefits (Anh et al., 2024; Ransbotham et al., 2017) [17] [18].

Organizations struggle to integrate new technologies such as BCT, leading to suboptimal performance and reduced competitive advantage (Noor, 2022) [19]. TCS, OGR, and competency insufficiency negatively impact employees' PU and PEOU, especially in non-Western contexts such as China.

Previous research has focused on integrating UTAUT in variables such as OGC, readiness, PEOU, and usefulness (Marchewka and Kostiwa, 2014) [20]. However, a gap exists in implementing this theory in variable TCS. Furthermore, an extensive examination of how organizations should prepare to manage and propose solutions for TCS has not yet been conducted. While there are many studies conducted on studying the significant factors such as PEOU and usefulness, OGC and readiness, and their impact on the BIU technology, there exists a distinguished gap in studying the moderating role of TCS negatively impacting the PEOU and usefulness and BIU BCT.

Objectives:

- To investigate how OGC and readiness influence BCT's PU and PEOU.
- To analyze the influence of PU and PEOU on the BIU BCT.
- To explore how techno stress affects PEOU, usefulness, and BIU technology.
- To verify how technostress moderates the implementation of BCT in organizations.

2 LITERATURE REVIEW

"Organizational competence" denotes an organization's core capabilities to accomplish its objectives (Taatila, 2004) [21]. According to Long et al. 2013 [16], OGC refers to the ability, knowledge, skills, and other relevant attributes an employee possesses to perform their work successfully. According to Ncube and Chimucheka (2019) [22], to enhance competency, it is necessary to enhance the performance of the workforce inside the organization. According to Herdinata et al. (2019) [23], how one uses technology depends on the organization's competence, expertise, support, and productivity level.

According to Ncube and Chimucheka (2019) [22], it is logical to believe that an organization would be considered competent if its personnel had the technical skills necessary to operate a system. On the other hand, employees who do not possess the technical expertise necessary to use a particular technology will not acknowledge the value of that technology (Maduka et al., 2018) [24].

OGR refers to the intensity to which an organization can make available resources necessary for implementing and using technology such as AI and BCT (Subhodeep Mukherjee et al., 2022) [25]. According to (Anh et al., 2024)[17]. Research findings show that the BIU technology is impacted by OGR, PEOU, and the availability of resources within the organization (Amalahmathi, 2023; Idris and Obansa Idris, 2014a) [26] [27]. These are essential elements that are crucial for determining OGR. When a company is not ready to implement revolutionary technologies such as BCT, employees will feel restricted and limited in their ability to use them, and they will not be able to take full advantage of their benefits (Yaqub and Alsabban, 2023) [28].

Perceived usefulness is a word coined by Davis (1986) [29] to describe the subjective beliefs held by users about how the usage of technology can enhance their ability to do tasks. Davis offers a similar explanation of PEOU, indicating that it pertains to an individual's conviction that utilizing a particular system or technology will necessitate low exertion. A study that was carried out by Tahar et al. (2020) [13]. According to the findings of this investigation, the PEOU and PU have a significantly favorable impact on the BIU technology. Subjective norms, image, job relevance, output condition, and result certitude are all components of PU. The ease of using technology directly influences user satisfaction, which is influenced by factors like PEOU, usefulness of the IT system, workgroup characteristics, attitude towards change, and job stress (D. Lee et al., 2009) [30]. A study in Indonesia found that the implementation of a digital payment app significantly influences BIU and PEOU, as well as PU's attitude towards technology use (Setiawan and Siregar, 2023) [31]. Basuki et al. (2022) [32] found that PEOU, usefulness, enjoyment, and intention to use online platforms significantly influence BIU in viewing online films. Ajzen (1991) [33] shows that consumers' intention to use a technology is determined by its PU. TCS, or technology dependence, is an emotional state defined by a person's persistent reliance on technology and anxiety when using technological tools such as AI or blockchain. (Belal Panahi, 2023) [14]. It can negatively impact job performance and employee behavior.

Khlaif et al. (2023) [34] and Youngkeun Choi (2023) [35] found that TCS negatively affects BCT's usefulness and ease of use. Shbail et al. (2023) [36] found positive attitudes towards technology adoption positively influence BIU adoption. Studies by Forough et al. (2020) [37] reveal that IT TCS negatively impacts employee compliance with information security procedures due to technological complexity, invasion, and insecurity.

It has also been found that TCS negatively impacts PEOU and usefulness, while psychological empowerment regulates this relationship (H. Lee and Kim, 2019) [38]. TCS negatively impacts users' satisfaction with ICT and task performance, reducing productivity and innovation (Monideepa Tarafdar et al., 2014) [39]. The study by Hashem Alshurafat et al. (2023) [40] showed that TCS significantly influences the PU and ease of use of BCT, affecting attitudes and BIU.

A positive relationship between PEOU and BIU is found in university academic portals, with PU not significantly influencing BIU. The study by Septiani et al. (2017) [41] explores user intentions towards GO-JEK, an Indonesian online transportation service. It utilizes IT adoption theories to analyze internal perception, external influences, innovation characteristics, enjoyment, and service variety. The research that was carried out by Ramllah and Ahmad Nurkhin (2019) [42] explores the impact that many aspects, including performance expectancy, effort expectancy, social influence, facilitating conditions, perceived credibility, and anxiety, play in determining the overall effectiveness of e-learning behavioral intention to use.

3 STUDY HYPOTHESES AND MODEL CONSTRUCTION

The Unified Theory of Acceptance and Use of Technology (UTAUT), proposed by Venkatesh, Morris, Davis, and Davis in 2003, specifically examines the direct influence of four important factors. The constructs referred to are performance expectancy, effort expectancy, social influence, and facilitating conditions. These constructs influence the perceived probability of adopting technology. The impact of the predictors is influenced by factors such as age, gender, experience, and voluntary use (Dwivedi et al., 2019) [43]. The BIU underpins the actual utilization of technology, according to the UTAUT theoretical paradigm. According to this theory, the variables of our research, namely OGC and Readiness, are considered as the facilitating conditions, as they provide the necessary skills and knowledge that are needed to make the use of technology easy and hence are regarded as a facilitating condition to BCT impacting the BIU and positively impacting the PEOU and usefulness. Similarly, the PEOU is considered as a construct that measures the expectation of effort in this theory. The reason for this is that the PU and BIU BCT are affected by the simplicity of the PEOU. PU is considered a performance construct according to UTAUT because if a person considers the fact that using BCT will enhance job performance, it will ultimately lead to a BIU and a positive attitude. So, in the context of this theory, performance expectancy leads to job satisfaction, gaining competencies, and motivation, which will impact BIU technology. Based on the discussion, the following hypotheses are proposed:

- H1: OGC positively influences the PU.
- H2: OGC positively influences the PEOU.
- H3: OGR positively influences the PU.
- H4: OGR positively influences the PEOU.
- H5: PU positively influences the BIU BCT.
- H6: PEOU positively influences the BIU BCT.
- H7: PU positively mediates between OGC and BIU BCT.
- H8: PU positively mediates between OGR and BIU BCT.
- H9: PEOU positively mediates between OGC and BIU BCT.
- H10: PEOU positively mediates between OGR and BIU BCT.

The proposed conceptual model integrates the elements of UTAUT, in which OGC and readiness are considered as the facilitating conditions in UTAUT, PU is considered as performance expectancy, PEOU is effort expectancy, and BIU BCT is the BIU element of UTAUT. The variable TCS is considered an external element that negatively affects performance and effort expectancy. The variable OGC is taken from the work of Chatterjee et al. (2021) [44] OGR is adapted from the studies of Esen and Özbağ (2014) [45]. The variables PEOU, PU, and BIU are taken from the studies of Wicaksono and Maharani (2020) [46]. The variable TCS is taken from the studies of Khlaif et al. (2023b) [47]. Previous studies did not discuss the TCS variable as a moderator, but our study fills this research gap. Figure 1 illustrates the proposed research model.

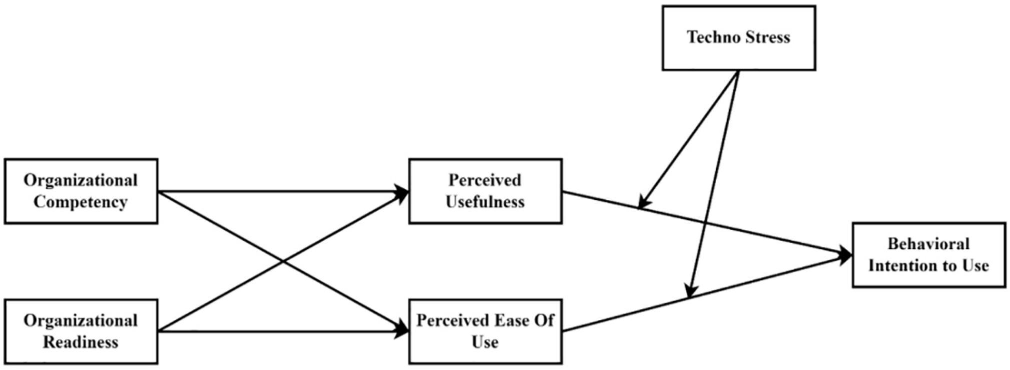

Fig. 1. Research model

4 STUDY DESIGN

The conceptual model and hypotheses were validated through surveys and a questionnaire created by academic scholars and IT specialists. The questionnaire, consisting of 44 items, was tested to ensure respondents understood and provided relevant answers. We employed a 5-point Likert scale, where a score of 1 denoted "strongly disagree" and a score of 5 denoted "strongly agree." The four questions for the variable OGC were taken from the studies of Choi Sang Long et al. (2019) [48]; for the variable OGR, the four questions were taken from the studies of Idris and Obansa Idris (2014b); Y. Lee et al. (2003); and Mohamed Gamal Aboelmaged (2014) [49] [50] [51]. The four questions for PEOU were adopted from the study of Davis (1989) [52], and the four questions for PU from studies of Y. Lee et al. (2003) [50], the 25 questions for TCS were taken from Tarafdar et al. (2007) [53]. Dependent variable BIU has three questions adopted from Maruping et al. (2017) and Venkatesh et al. (2003) [54] [55].

The study utilized convenience sampling to gather data on technology adoption experts in Chinese enterprises, obtaining 405 responses. 380 authentic responses were selected for analysis using the SEM technique based on partial least squares, which yields better results for exploratory studies and a large sample size (Anam Alina et al., 2023; Hair Jr. et al., 2016a; Hameed et al., 2023; Jahangir et al., 2022, 2024; Manzoor and Jahangir, 2023) [56] [57] [58] [59] [60] [61]. The survey was conducted without sample restrictions and quantified responses using a specific scale.

5 EMPIRICAL TESTS

The demographic analysis of the study is shown in Table 1. The proportion of male participants (76%) is slightly higher than that of female participants (24%). The age distribution demonstrates a diverse variety of professional experience levels. The largest group consists of individuals aged 26–35 years, accounting for 45.26% of the total. This is followed by those aged 18–25 years, making up 27.11% of the total, and individuals aged 36–45 years, comprising 22.89% of the whole. A significant percentage of persons in the sample hold Bachelor's degrees (45%) and Master's degrees (38.68%). This suggests that the sample possesses a high level of education. Technical staff and IT administrators and supervisors make considerable contributions, with 54.47% and 33.95%, respectively. The sample, predominantly educated with Bachelor's and Master's degrees, includes technical staff, IT administrators, and supervisors, providing a comprehensive view of technology adoption among Chinese enterprise professionals.

Table 1. Demographics analysis

Demographics	Frequency	Percentage
Gender		
Male	289	76%
Female	91	24%
Age Group	**380**	100%
18–25 years	103	27.11%
26–35 years	172	45.26%
36–45 years	87	22.89%
46–55 years	15	3.95%
56 years and above	3	0.79%
Total	380	100.00%
Education Level		
High School	60	15.79%
Bachelor's Degree	171	45.00%
Master's Degree	147	38.68%
Doctorate/Ph.D.	2	0.53%
Total	380	100.00%
Occupation		
Technical Staff/IT Administrators	207	54.47%
Supervisors	129	33.95%
Manager	31	8.16%
Director	13	3.42%
Total	380	100.00%

Table 2 displays the correlation coefficients between the observed variables (items) and the corresponding latent constructs (variables). Each component of a build possesses a factor loading value, and all of these values exceed 0.7 (Hair Jr. et al., 2016b) [62]. Therefore, this indicates that the items possess a robust representation of their respective structures, which is a compelling illustration of convergent validity. The greater loadings of the items show their effectiveness as indicators of the latent variable.

Table 2. Factor loadings

Variable	Item	Loading
OGC	OGC1	0.703
	OGC2	0.721
	OGC3	0.750
	OGC4	0.774
OGR	OGR1	0.710
	OGR2	0.736
	OGR3	0.762
	OGR4	0.780

(Continued)

Table 2. Factor loadings *(Continued)*

Variable	Item	Loading
PU	PU1	0.741
	PU2	0.768
	PU3	0.781
	PU4	0.790
PEOU	PEOU1	0.704
	PEOU2	0.720
	PEOU3	0.745
	PEOU4	0.755
BIU	BIU1	0.780
	BIU2	0.806
	BIU3	0.820
TCS	TCS1	0.701
	TCS2	0.713
	TCS3	0.715
	TCS4	0.720
	TCS5	0.736
	TCS6	0.740
	TCS7	0.756
	TCS8	0.760
	TCS9	0.776
	TCS10	0.784
	TCS11	0.793
	TCS12	0.802
	TCS13	0.812
	TCS14	0.823
	TCS15	0.837
	TCS16	0.843
	TCS17	0.851
	TCS18	0.860
	TCS19	0.879
	TCS20	0.880
	TCS21	0.891
	TCS22	0.903
	TCS23	0.914
	TCS24	0.923
	TCS25	0.939

The cumulative factor analysis is shown in Figure 2.

All the constructs in the data reliability and validity table have Cronbach's alpha scores more than 0.7, indicating that they possess sufficient levels of internal consistency and reliability. Furthermore, the composite reliability (CR) values surpass the threshold of 0.7, indicating the excellent reliability of each construct. The values of the average variance extracted (AVE) being greater than 0.5 indicate that each construct can capture a significant amount of variance from its indicators, surpassing the variance caused by measurement error. This suggests strong convergent validity. All these values are shown in Table 3.

According to the Fornell-Larcker criterion used in the discriminant validity Table 4, the square root of AVE (highlighted diagonal values) should be greater than the correlations (off-diagonal values) with other variables. The fulfillment of this criterion by each construct in the table serves as proof that each construct is distinct from the others. The values indicate that the constructs measure distinct concepts, thereby demonstrating the strong discriminant validity of the constructs.

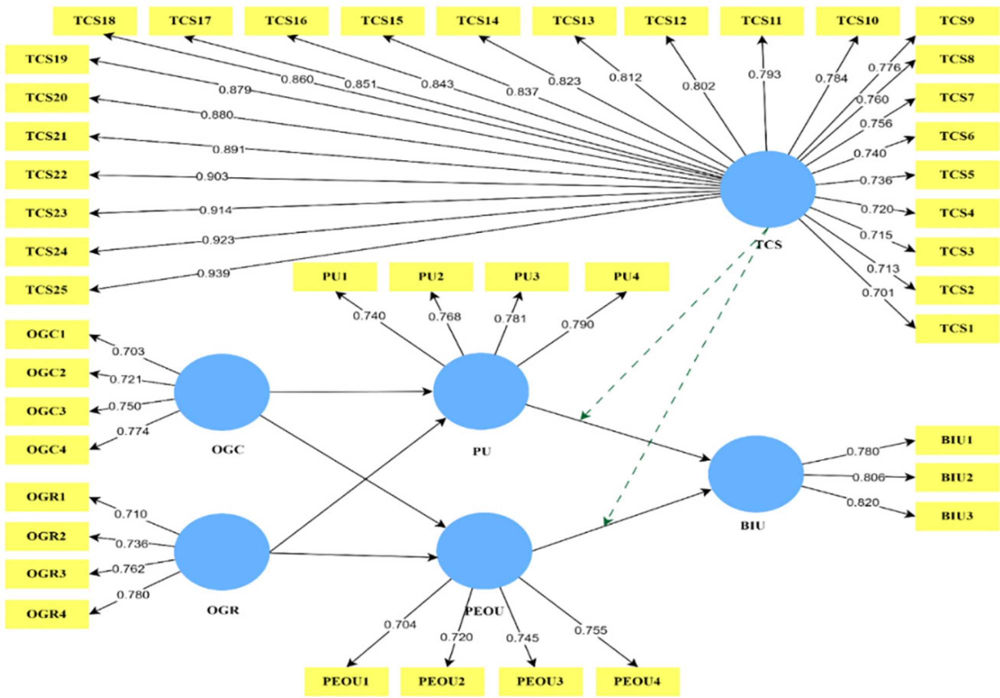

Fig. 2. Cumulative factor analysis

Table 3. Data reliability and validity

Variable	Cronbach Alpha	CR	AVE
OGC	0.800	0.850	0.600
OGR	0.820	0.870	0.620
PU	0.810	0.860	0.610
PEOU	0.790	0.840	0.590
BIU	0.830	0.880	0.630
TCS	0.900	0.920	0.680

Table 4. Discriminant validity

Constructs	OGC	OGR	PU	PEOU	BIU	TCS
OGC	**0.770**					
OGR	0.650	**0.790**				
PU	0.550	0.600	**0.780**			
PEOU	0.520	0.540	0.590	**0.770**		
BIU	0.500	0.530	0.560	0.580	**0.790**	
TCS	0.450	0.480	0.500	0.520	0.540	**0.820**

The R-square values in Table 5 indicate the proportion of the variation in the dependent variable that the independent variables can explain. Regarding PU, an R-square value of 0.50 signifies that the independent factors explain fifty percent of the variation. Similarly, the R-square value for PEOU is 0.45, while the R-square value for BIU is 0.55. Based on these findings, the model demonstrates a level of explanatory capability that varies from moderate to high for various constructs (Hair, Hult, Ringle, 2013; Hair Jr. et al., 2016b; Jahangir et al., 2022) [63] [62] [59].

Table 5. R-square values

Variable	R Square
PU	0.500
PEOU	0.450
BIU	0.550

The model's fit values are displayed in Table 6, which contains various indices that can be used to assess the level of agreement between the model and the data being provided. The chi-square value of 250.34, although it should ideally be lower, is corroborated by other indices such as SRMR (0.04), D_ULS (1.25), and d_G (0.90), all of which suggest that there is a satisfactory alignment between the two datasets. The NFI value of 0.91, the CFI value of 0.95, and the TLI value of 0.94 all surpass the criterion of 0.90, indicating that the fit is considered adequate. The observed data and the model exhibit a strong correspondence, as evidenced by the RMSEA value of 0.05 falling inside the acceptable range. Overall, these findings indicate that the model accurately represents the data satisfactorily.

Table 6. Model fit values

Measure	Value
Chi-square	250.340
SRMR	0.040
D_ULS	1.250
d_G	0.900
NFI	0.910
CFI	0.950
TLI	0.940
RMSEA	0.050

A direct path analysis table is a tabular representation that presents the coefficients, t-values, and p-values for the direct correlations between variables. A positive coefficient indicates a positive connection. An example is the observation that OGC positively affects PU with a coefficient of 0.30, a t-value of 3.50, and a p-value less than 0.001. This suggests that OGC substantially impacts PU or the PU. Similarly, the remaining paths, including OGC -> PEOU, OGR -> PU, and PU -> BIU, exhibit statistical significance with p-values below 0.005. This suggests that these relationships are statistically significant. All these relationships are specified in Table 7.

Table 7. Direct path analysis

Path	Coefficient	t-value	p-value	Decision
OGC -> PU	0.300	3.500	0.001	Positively Accepted
OGC -> PEOU	0.350	4.000	0.000	Positively Accepted
OGR -> PU	0.250	2.800	0.005	Positively Accepted
OGR -> PEOU	0.280	3.200	0.002	Positively Accepted
PU -> BIU	0.400	4.500	0.000	Positively Accepted
PEOU -> BIU	0.350	4.000	0.000	Positively Accepted
TCS -> BIU	–0.22	–3.140	0.003	Positively Accepted

The mediating path analysis Table 8 illustrates the indirect influence of independent factors on the dependent variable, facilitated by mediators. For example, the route from OGC to PU to BIU has a statistically significant indirect impact of 0.12, with a standard error of 0.03. The path has a t-value of 4.00, and the p-value is less than 0.001. One possible inference is that the perception of utility influences the connection between OGC and BIU. The significance of other mediating paths, such as OGC -> PEOU -> BIU and OGR -> PU -> BIU, supports the premise that PU and PEOU mediate the interaction.

Table 8. Mediating path analysis

Path	Indirect Effect	SE	t-value	p-value	Decision
OGC -> PU -> BIU	0.120	0.030	4.000	0.000	Positively Accepted
OGC -> PEOU -> BIU	0.140	0.040	3.500	0.001	Positively Accepted
OGR -> PU -> BIU	0.100	0.030	3.330	0.001	Positively Accepted
OGR -> PEOU -> BIU	0.120	0.030	4.000	0.000	Positively Accepted

Table 9. Moderating path analysis

Path	Interaction Effect	SE	t-value	p-value
PU * TCS -> BIU	–0.15	0.05	–3.00	0.003
PEOU * TCS -> BIU	–0.18	0.06	–3.00	0.003

The moderating path analysis Table 9 demonstrated that TCS substantially negatively impacts the relationships between the mediators (PU and PEOU) and the dependent variable (BIU). The findings suggest that TCS moderates the relationship between PU and BIU, as seen by a negative interaction impact of –0.150, indicating a detrimental influence. This demonstrates that increased concentrations of TCS have a detrimental effect on PU's advantageous influence on BIU.

The path analysis results are shown in Figure 3.

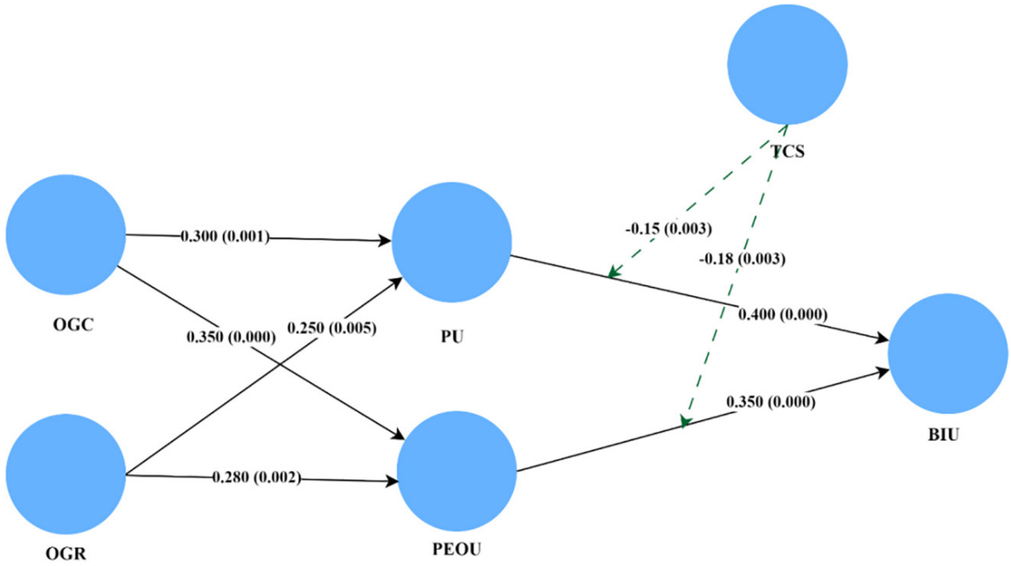

Fig. 3. Path analysis

The negative moderation effect of TCS on the relationship between PEOU and BIU is evident from the negative interaction impact, which has a value of –0.180. Considering this, it can be inferred that higher concentrations of TCS have a detrimental impact on the advantageous effects of PEOU on BIU. Table 9 shows the moderating path analysis, while Figure 4 shows the moderating graph.

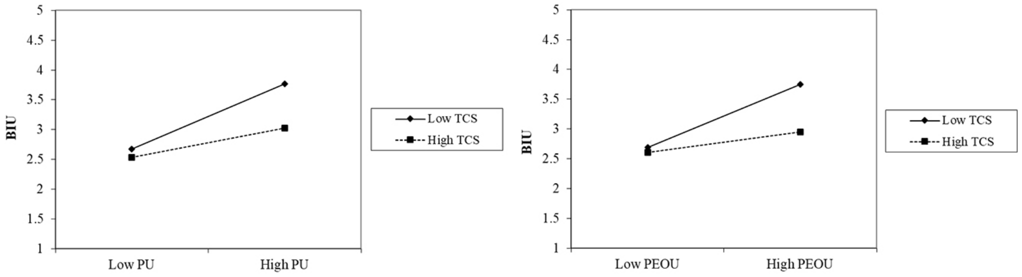

Fig. 4. Moderating graph

6 DISCUSSION

The result shows that OGC positively influences PU, thus supporting Hypothesis H1. This shows that the company's workforce has the necessary abilities, knowledge, skills, and other qualities needed to produce efficient work that will benefit the company. Recent studies by Donghun (Don) Lee et al., (2017) and Long et al., (2013) [64] [16] also supports this hypothesis (i.e., H1), i.e., that an organization's competency helps employees focus on job-related information and enhances the performance of the organization's employees. Results also show that OGR positively affects PU, supporting our hypothesis. This confirms the findings of earlier studies. Ransbotham et al., (2017) [18], found that there will not be any barriers to the adoption of new technologies provided appropriate financial, technical, and human resources are available. However, the results also show that OGR positively impacts PEOU. The study showed positive results in the relationship between PEOU and behavioral intention to adopt BCT and the positive impact of PU and the behavioral intention to adopt BCT. All these findings conform with the concept of TAM and UTAUT (Davis, 1986) [29]. Similarly, our results confirm the hypothesis that TCS significantly moderates the relationship between PEOU and BIU BCT and between PU and BIU BCT, showing that a high level of TCS in organizations weakens the positive effect of PEOU, usefulness, and BIU BCT.

7 CONCLUSION

This study extended the UTAUT theory by incorporating TCS as an external variable to study the BIU BCT in Chinese companies. The study's results show the moderating role of TCS in the relationship between PEOU and BIU BCT and PU and BIU BCT. Along with this, the research highlighted the positive impact of OGR and competency on PEOU and usefulness, keeping in view the previous studies that support this relationship. This study offers a complete framework for understanding companies' acceptance of BCT. It puts a particular focus on the role of reducing TCS and improving OGR in order to support the effective implementation of technology.

8 IMPLICATIONS

Organizations should focus on improving competency and readiness for new technologies and investing in infrastructure and training programs. Managing TCS can mitigate its adverse effects by providing stress management programs, technical support, and work-life balance. User-centric design principles should be prioritized for improved usability and satisfaction. Customized interventions such as routine evaluations are essential for employees with high TCS levels.

9 THEORETICAL IMPLICATIONS

The extended UTAUT model is validated by incorporating TCS as an external variable, affecting performance expectancy, effort expectancy, and BIU. This extension provides a comprehensive understanding of factors influencing technology adoption, particularly in the Chinese cultural context.

10 LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

The study provides valuable insights into the impact of technology adoption in Chinese culture, but its findings are not universally applicable. The study examines TCS as a single psychological construct, neglecting other potential moderating variables like individual and organizational factors. Future research should explore these factors independently for a more comprehensive understanding.

11 FUNDING

This study is supported by the National Social Science Fund of China (No. 20BGL218; Title: Research on the Application of Alliance Blockchain in the Governance Innovation of Internet Hospitals).

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