International Journal of Advances in Data and Information Systems
Vol. 5, No. 2, October 2024, pp. 123~135
ISSN: 2721-3056, DOI: 10.59395/ijadis.v5i2.1321

Adoption Drivers of Digital Platform for Coal Production Planning: an Extended UTAUT Model Using PLS-SEM Analysis

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Article Info

Article history:

Received Jun 04, 2024
Revised Sep 09, 2024
Accepted Oct 30, 2024

Keywords:

Digital Platforms,
Production Planning,
Technology adoption,
UTAUT,
PLS-SEM,
Information Systems

ABSTRACT

In 2022, the coal production industry encountered unprecedented challenges accompanied by a substantial global commodity price surge. The operational impact of this situation surpasses current technological capabilities of coal companies, particularly in optimizing coal blending scenarios. A pivotal aspect of digital transformation involves integration of new digital platform for production planning. This study employs the Unified Theory of Acceptance and Use of Technology in conjunction with decision theory to identify key factors influencing the platform adoption at a coal mining company. Structured questionnaires were utilized, followed by analysis using the SmartPLS 4.0.9.9 software. Findings reveal that both Performance Expectancy and Effort Expectancy positively influence users' behavioral intention to adopt digital platform for production planning. Behavioral Intention, in turn, significantly impacts actual usage behavior. Unanticipated situational factors and others' attitudes were found to have negligible mediating effects, while variables such as age and experience showed no moderating influence on the pathways from behavioral intention to usage behavior. Companies are advised to improve digital platform performance through functionalities enhancements and pilot testing to reduce perceived effort and stimulate behavioral intention. Additionally, fostering a positive organizational mindset through routine motivational communications can further stimulate usage behavior.

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1. INTRODUCTION

In 2022, the coal industry faced challenges in achieving production targets due to a substantial increase in global prices. Despite the upward trend in prices, operations struggled to meet their goals, leading to concerns about fulfilling demand and capitalizing on favorable market conditions. The situation was further complicated by unexpected consequences. Instead of optimizing profits from the price index spike, demurrage and penalty expenses increased significantly. This unanticipated rise in extra costs was a major setback that affected overall profitability and hindered the company from fully capitalizing on the upward price trend. To maximize income and minimize potential losses, the company had to carefully balance meeting production targets with controlling associated costs.

The complexity of the coal industry exceeds the capabilities of the current technology used to compute ideal blend scenarios. The number of criteria required to determine the optimal blend composition are often too complex for traditional approaches to manage with the necessary agility and computational capacity.

Consequently, businesses may find it challenging to maximize the value of their coal resources and optimize operational efficiency. Moreover, the goal of maximizing revenue can impact profit margins. Therefore, achieving a sustainable business model where revenue generation aligns with maintaining healthy profit margins necessitates finding the right balance between these two objectives.

Current technology used to determine the best blend scenarios in the coal industry is unable to handle the complex problems specific to the sector. Conventional approaches lack the necessary flexibility and processing capacity to navigate the numerous parameters involved in determining the optimal blend composition. This technological deficiency has been a major obstacle, preventing the industry from effectively responding to the complications arising from changing market conditions.

Over the past few years, PT. CKPE, an anonimized coal company, has been pursuing technical improvements to enhance operating procedures and efficiency. The program began with the creation of digital platform for production planning designed to shift from Excel-based tasks to an electronic, auditable tool called Mine Track. Unfortunately, this initial attempt was not as effective as planned due to implementation issues. Despite this setback, the company persisted, releasing more applications that also encountered problems during installation. This led to a narrative of technological optimization through trial and error.

The IT department faced challenges understanding the complexities of the backend program, impacting their ability to provide sufficient support. As a result, the development process did not adequately meet user requirements, affecting the technology's successful application. High dependencies and the need for numerous licenses to run interfaces further complicated the development process. These problems were categorized into several areas: a gap between project goals and users' actual needs, operational difficulties, high technical support dependencies, and lack of stakeholder involvement. This complexity made the adoption process more challenging and prevented smooth integration. To successfully implement technology, PT. CKPE must overcome these obstacles by using a comprehensive approach that closes communication gaps, improves IT capabilities, and ensures the development process closely aligns with user needs.

While most of the literature[1][2], [3], [4] focuses on the integration of pre-existing theories like UTAUT, or TPB, this study new perspective by combining UTAUT (Unified Theory of Acceptance and Use of Technology) with the Purchase Decision framework. Methodologically, this study adopts a unique focus by including the Purchase Decision framework, whereas other publications utilize known theoretical frameworks to investigate different aspects of technology adoption and behavior intention.

For instance, Cobelli's study on pharmacists' attitudes toward telemedicine highlights the positive correlation between market orientation and performance and effort expectancy, while noting a negative impact on facilitating conditions, influencing adoption intentions for telemedicine service providers [1]. Huang's research on VR tourism underscores the influence of perceived benefits on behavior, strengthening the connections between UTAUT components [5]. Van der Waal's integrative approach to contact tracing app adoption shows that combining UTAUT, Health Belief Model (HBM), and contextual factors results in a better model fit, with all variables significantly predicting adoption [6]. Alkhowaiter's study on mobile payments in GCC nations reveals the crucial roles of trust and Islamic religiosity as moderating variables [7]. Azman Ong's study on digital payment systems among rural residents identifies social influence, effort expectancy, and epistemic value as key factors influencing behavioral intention, while Singh's investigation into online class adoption highlights the digital divide as a significant barrier to education [2], [8]. Bellet's study on automated vehicle adoption demonstrates the robustness of the UTAUT4-AV model in predicting intention across various types of automated vehicles, and Gao's investigation into smart education continuance intention clarifies the crucial role of the flow state in strengthening intention [3], [4].

Acknowledging previous studies, this study offers a different viewpoint by addressing the complex dynamics that drive employee attitudes and adoption behaviors in a corporate context. Identifying and describing the specific factors that influence behavior use in the coal mining industry is particularly challenging due to the unique business models, internal technology applications, varying personnel ages, male-dominated workforce, and limited experience with the application. Thus, the research question for this study is:

"What are the primary factors that facilitate the adoption of a digital platform for production planning at PT. CKPE?"

2. LITERATURE REVIEW

2.1 Technology Adoption Model

To explain user adoption of new technologies, several models and frameworks have been developed. These include the Technology Acceptance Model (TAM), the Theory of Planned Behavior (TPB), the Diffusion of Innovation Theory (DOI), the Theory of Reasoned Action (TRA), the Model of PC Utilization (MPCU), the Motivational Model (MM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Social Cognitive Theory (SCT). Numerous studies have utilized these conventional frameworks, while others have combined existing models or introduced new constructs to enhance their research.

To fully comprehend the multifaceted issues surrounding technology adoption, it is essential to consider multiple theoretical perspectives. Each method is discussed separately for clarity. Various theoretical approaches, such as the Innovation Diffusion Theory (IDT), TIB, TPB, and SCT, are rooted in psychosocial theories and sociology, while the Theory of Reasoned Action (TRA) stems from social psychology. However, TRA and TPB differ from DOI in focusing on individual behavior.

Many information system researchers have not differentiated between the cognitive component (beliefs) and the affective component (attitudes, which have a like/dislike connotation). Beliefs are the facts an individual holds about a person, thing, or topic. According to Perlusz, behaviors are influenced by both emotional and affective components, as well as cognitive processes. Historically, most technology adoption theories have largely ignored emotions and feelings. With few exceptions, such as Venkatesh [9], most models use only cognitive predictors to link attitudes, beliefs, and perceptions to the adoption and real-world use of new technologies [10].

2.2 Unified Theory Acceptance and Use of Technology

Venkatesh [9] introduced the Unified Theory of Acceptance and Use of Technology (UTAUT), which identifies four major dimensions as direct predictors of usage intention and behavior: performance expectancy, effort expectancy, social influence, and facilitating conditions. In UTAUT, performance expectancy is defined as "the degree to which an individual believes that using the system will help him or her attain gains in job performance," a concept similar to TAM's perceived usefulness [11]. The UTAUT model suggests that behavioral intention determines the actual use of technology, influenced by these four key constructs. The effects of these predictors are moderated by age, gender, experience, and voluntariness of use [9].

The strength of these predictors on intention is moderated by age, gender, experience, and voluntariness of use. Age moderates all four factors, while gender influences the relationships between effort expectancy, performance expectancy, and social influence. Experience moderates the linkages between social influence, facilitating conditions, and effort expectancy. Voluntariness of use specifically modifies the association between social influence and behavioral intention. Venkatesh [9] emphasize that the acceptance process of technology is complex, demonstrating interactive influences of constructs with personal and demographic aspects, such as age, gender, and level of expertise [11].

In this study, we define several hypotheses for the adoption of digital platform for production planning. The first one is on performance expectancy. Performance expectancy is the belief that using a new tool or technique will enhance one's efficiency or output. It is defined as the confidence that using a particular system will improve job performance. We define the hypothesis as follows:

H_1: *Performance expectancy has a positive effect on users' behavioral intention to adopt a digital platform for production planning.*

The second one is on effort expectancy. According to Venkatesh [9], effort expectancy is the perceived ease of using a system. This construct is particularly important when users are attempting a new activity and facing the initial challenges of learning it. We define the hypothesis as follows:

H_2: *Effort expectancy has a positive effect on users' behavioral intention to adopt a digital platform for production planning.*

The third one is on effort expectancy. Cai [12] describe social influence as the extent to which an individual perceives that important others believe they should use the new system. It also encompasses the individual's influence over others regarding the use of the system.

H_3: *Social influence has a positive effect on users' behavioral intention to adopt a digital platform for production planning.*

Next is on facilitating conditions. Facilitating conditions are defined as the belief that the technological infrastructure exists to support system usage [9].

H_4: *Facilitating conditions positively influence users' behavioral intention to adopt a digital platform for production planning.*

Penultimately is the evaluation of alternatives. The evaluation of alternatives, based on the characteristics of the task and the technology, refers to the degree to which the features and supports of the technology meet the requirements of the task [9]. Technological characteristics like reliability and performance form the basis for this evaluation.

H_5: *Facilitating conditions positively influence users' behavioral intention to adopt a digital platform for production planning.*

Ultimately is the behavioral intention. It is the intention to use a system and is a direct predictor of actual usage behavior.

H_6: *Behavioral intention positively influences the use of a digital platform for production planning.*

2.3 Purchase Decision

Customers do not always follow a single decision-making rule when choosing what to buy. Instead, they may use a staged approach involving multiple decision rules. For example, they might initially use a noncompensatory decision process, such as the conjunctive heuristic, to narrow down the number of brand options. Then, they may evaluate the remaining brands using a compensatory model. Two general factors can influence buying intention and purchase choice even after customers have formed brand assessments: the attitudes of others and perceived risk.

Attitudes of Others, the influence of other people's attitudes on a consumer's choice depends on two factors (1) The Degree of Negative Perception, how strongly the other person views the consumer's chosen alternative negatively. (2) Willingness to Accommodate, he consumer's readiness to consider the other person's preferences. The consumer's intention to purchase will be adjusted based on how personal and significant the other person's dislike is. This influence works both ways—if others have a positive attitude towards the choice, it can reinforce the consumer's intention. Infomediaries, who share their evaluations, also play a role similar to personal influences.

H_7: *The attitudes of others have a mediating influence on the use of behavior for adopting a digital platform for production planning.*

Perceived risk significantly affects a consumer's decision to modify, postpone, or avoid a purchase. Different types of risks include: (1) Functional Risk, where the product may not perform as expected; (2) Physical Risk, where the product could harm the user's or others' physical well-being; (3) Financial Risk, where the product might not be worth the money spent; (4) Social Risk, where the product may cause embarrassment; (5) Psychological Risk, where the product could impact the user's mental health; and (6) Time Risk, where if the product fails, there is a cost associated with not finding a better product. The degree of perceived risk varies with the amount of money at stake, attribute uncertainty, and user self-confidence. To reduce risk, customers establish routines such as avoiding decisions, seeking information from friends, and preferring national brand names and warranties [13].

H_8: *Unanticipated situational factors have a mediating influence on users' behavior in adopting a digital platform for production planning.*

Age, Gender, and Experience. Research indicates that gender roles have a stable psychological foundation but can change over time [9]. Similarly, age is believed to moderate the relationship between key constructs and behavioral intention. Studies show that younger employees might value external advantages more, while older workers may place more emphasis on social factors, with this effect decreasing with experience [9].

H_9 : *Age, gender, and experience will moderate the relationship between effort expectancy and behavioral intention in the adoption process.*

H_{10}: *Age, gender, and experience will moderate the relationship between social influence and behavioral intention in the adoption process.*

H_{11}: *Age and experience will moderate the relationship between social influence and behavioral intention in the adoption process.*

H_{12}: *Age and experience will moderate the relationship between facilitating conditions and behavioral intention in the adoption process.*

To summarize, we portray a theoretical conceptual model as depicted in Figure 1.

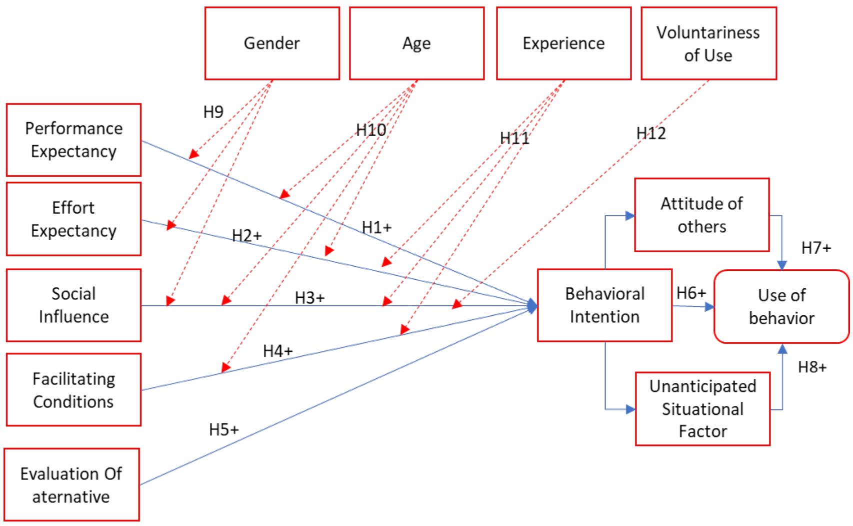

Fig 1. Theoretical Conceptual Model

3. METHOD

This study employs a quantitative research approach to investigate the factors influencing the adoption of a digital platform for production planning. This approach enables a structured and systematic analysis of the variables, contributing to literature by highlighting the relationships between variables and identifying the motivational patterns associated with the adoption of digital production platforms within the coal mining industry. To the best of our knowledge, this method has not been previously applied in the coal mining industry.

The author collected two types of data: primary and secondary. The primary data was gathered using a questionnaire designed based on a thorough synthesis of relevant research (see Appendix 1). The Likert scale used in the questionnaire was interpreted as follows: 1 - Strongly Disagree; 2 - Disagree; 3 - Neutral; 4 - Agree; 5 - Strongly Agree. The questionnaire development was carefully aligned with the study's topic, drawing inspiration from various journal sources. User technology acceptance was measured using variables (22 items) from the UTAUT model [1], [2], [8], [12]. Evaluation of alternatives (5 items) was sourced from Cai [12], and attitudes of others (4 items) and unanticipated situational factors (8 items) were sourced from Huang [5].

The questionnaire was distributed to 77 prospective members of the PT. CKPE production team, essential to the manufacturing process flow plan. Respondent selection followed the internal production standard reference, ensuring the designation of personnel accountable for strengthening the success of the adoption of digital platform for production planning at PT. CKPE. Despite scheduling challenges, 40 responses were received during the data collection period from December 2023 to January 2024. This number of responses met the minimum sample size requirements based on the inverse square root method proposed by Kock and Hadaya [14], with a path coefficient between variable constructs of 0.31-0.4 and a significance level of 5%.

The analysis was conducted using Smart PLS 4.0.9.9, demonstrating the application of advanced tools for reliable data processing and interpretation. The assessment process involved evaluating both reflective and formative measurement models to determine the model's validity, reliability, and structural linkages. Internal consistency and indicator reliability were evaluated for reflective measurement models. Indicator reliability required loadings greater than 0.708, indicating that the construct explains more than half of the variation in the indicator. Internal consistency reliability, as determined by Cronbach's alpha, was within acceptable bounds for exploratory research and satisfactory to excellent for more established research. Convergent validity, an essential component of reflective measurement, was assessed using the average variance extracted (AVE), with a value of 0.50 or above considered good. Discriminant validity was evaluated using the heterotrait–monotrait (HTMT) ratio of correlations, with a threshold value of 0.90.

For formative measurement models, convergent validity was determined by evaluating the correlation between the formative construct and a reflectively measured variable of the same concept, with a correlation greater than 0.708 considered indicative of convergent validity. Collinearity issues were assessed using the variance inflation factor (VIF), with values between three and five considered non-problematic. Indicator weights were tested for significance using bootstrapping, comparing t-values to critical values. At a significance level of 5%. Indicators with loadings of at least 0.50 and statistical significance were considered relevant for further examination.

4. DATA

The survey participants exhibited a variety of attributes, including age, gender, level of expertise, and formal IT education. In terms of gender, 83% of the sample were men, and 18% were women. The respondents' ages varied widely: 28% were between 26 and 35 years old, 48% were between 36 and 45 years old, and 23% were between 46 and 55 years old. When evaluating IT skill levels, the distribution showed a range of proficiencies. Of the respondents, 13% considered themselves to have advanced IT skills, while 40% identified as beginners who primarily used basic programs to support their work. A small minority, 3%, regarded themselves as experts and were available as resources for IT issues, while the majority, 45%, were at an intermediate level and actively engaged in furthering their studies in the subject. Regarding formal IT education, 25% of participants had completed formal IT education, while the remaining 75% had not pursued formal IT education.

Table 2. Respondents

Characteristic	Frequency (n)	Percentage
Gender		
Man	33	83%
Female	7	18%
Age		
> 55	1	3%
26 - 35	11	28%
36 - 45	19	48%
46 - 55	9	23%
Skill		
Advanced: Proficient in the field of IT	5	13%

Beginner: Basic application to support work	16	40%
Expert: A reference for IT problems	1	3%
Intermediate: Currently studying the field of IT	18	45%
Has formal study in IT		
Yes	10	25%
No	30	75%

5. ANALYSIS

Partial Least Squares Structural Equation Modeling (PLS-SEM) was used to process all of the collected data. In the first stage, the author created the initial path model using the purchasing decision combined with the Unified Theory of Acceptance and Use of Technology (UTAUT). In this model, the UTAUT components were moderated by gender, age, experience, and voluntariness, and the mediating variables were attitudes of others and unexpected situational factors.

However, there was an issue with using Smart PLS v4.0.9.9 to process the initial route model. A singular matrix issue was detected by the software when the PLS-SEM algorithm was calculating. This problem occurs when calculating the inverse of a matrix, such as in the case of correlations and regression coefficients. This issue could arise from several factors, such as a variable having zero variance, extremely high levels of variable collinearity, or a sample size that is too small to enable the analysis. The author chose to intentionally remove potential variables that could lead to singularity in order to address the singularity problem that arose during the analysis of data collected from respondents. The review of respondent profiles showed that there was insufficient diversity in the respondents' gender variation, which was 18% female against 83% male. Since the " digital platform for production planning" was the only program available within the organization, users could not choose not to use it, so the variable "voluntariness of use" was also ruled not applicable. The author tried to improve the robustness of the data analysis and eliminate the singularity issue by removing some variables that were identified. The next observations are made following illustrating measurement models are assessed in relation to partial least squares structural equation modeling (PLS-SEM), as shown in Figure 3.

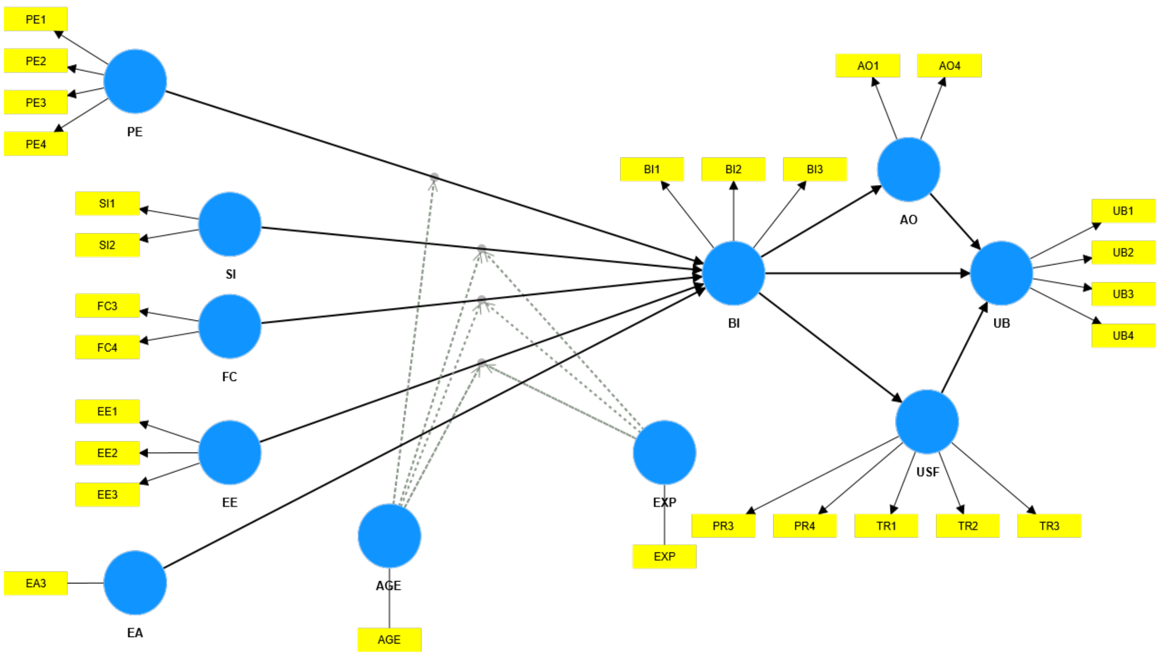

Fig 3. Adjusted Measurement Model Mapping Manifest Variables (MV) to Latent Variables (LV)

Performance Expectancy (PE) exhibits strong outer loadings, ranging from 0.899 to 0.936 across its indicators (PE1, PE2, PE3, PE4). The construct demonstrates a high level of internal consistency with a Cronbach's alpha of 0.933, indicating reliability. Additionally, the composite reliability (rho_c) of 0.952 reinforces the reliability of PE across its indicators, while the AVE of 0.833 signifies substantial variance captured by the construct. Social Influence (SI) exhibits robust associations with its indicators (SI1, SI2), reflected in outer loadings of 0.914 and 0.947. The construct maintains a high internal consistency with a Cronbach's alpha of 0.848, affirming internal consistency. The composite reliability (rho_c) of 0.929 is higher than the threshold of 0.7, suggesting good internal consistency. The AVE of 0.867 underscores the good convergent validity of SI.

Facilitating Condition (FC) shows strong outer loadings of 0.929 and 0.730 for its indicators (FC3 and FC4, respectively). Although the composite reliability (rho_c) of 0.820 and Cronbach's alpha of 0.596 suggest acceptable internal consistency, the AVE of 0.698 indicates the construct's ability to capture a significant amount of variance. Effort Expectancy (EE) demonstrates robust outer loadings (ranging from 0.847 to 0.937) across its indicators (EE1, EE2, EE3), affirming the reliability and validity of the construct. EE exhibits a high internal consistency with a Cronbach's alpha of 0.878 and a composite reliability (rho_c) of 0.924, while the AVE of 0.803 suggests substantial variance captured. Unanticipated Situational Factor (USF) shows varying outer loadings across its indicators (PR3, PR4, TR1, TR2, TR3). The construct shows a good level of internal consistency with a Cronbach's alpha of 0.795 and a composite reliability (rho_c) of 0.860. The AVE of 0.555 passes the convergent validity threshold. Attitude of Others (AO) exhibits strong outer loadings (0.749 to 0.898) across its indicators (AO1, AO4). Although the Cronbach's alpha of 0.551 is low, the composite reliability remains high at 0.811, indicating moderate internal consistency. Meanwhile, an AVE of 0.683 indicates good convergent validity; the lower Cronbach's alpha compared to other constructs suggests potential for improvement. Behavioral Intention (BI) demonstrates strong outer loadings (ranging from 0.877 to 0.949) across its indicators (BI1, BI2, BI3). The construct exhibits a high internal consistency with a Cronbach's alpha of 0.912 and a composite reliability (rho_c) of 0.945, while the AVE of 0.851 suggests substantial variance captured. Use of Behaviour (UB) displays robust outer loadings (ranging from 0.712 to 0.929) across its indicators (UB1, UB2, UB3, UB4). UB demonstrates good internal consistency with a composite reliability (rho_c) of 0.920. The AVE of 0.743 indicates good convergent validity.

Table 3. PLS-SEM Output

Construct	Outer loadings	Outer loadings	α	CR	(AVE)
Performance expectancy	PE1 <- PE	0.91	0.93	0.95	0.83
	PE2 <- PE	0.91			
	PE3 <- PE	0.94			
	PE4 <- PE	0.90			
Social Influence	SI1 <- SI	0.91	0.85	0.93	0.87
	SI2 <- SI	0.95			
Facilitating Condition	FC3 <- FC	0.93	0.60	0.82	0.70
	FC4 <- FC	0.73			
Effort Expectancy	EE1 <- EE	0.90	0.88	0.92	0.80
	EE2 <- EE	0.85			
	EE3 <- EE	0.94			
Evaluation of Alternative	EA3 <- EA	1.00			
Unanticipated Situational Factor	PR3 <- USF	0.84	0.79	0.86	0.55
	PR4 <- USF	0.82			
	TR1 <- USF	0.65			
	TR2 <- USF	0.61			
	TR3 <- USF	0.77			
Attitude of Others	AO1 <- AO	0.90	0.55	0.81	0.68
	AO4 <- AO	0.75			
Behavioral Intention	BI1 <- BI	0.94	0.91	0.94	0.85
	BI2 <- BI	0.95			
	BI3 <- BI	0.88			
Use Of Behaviour	UB1 <- UB	0.93	0.88	0.92	0.74
	UB2 <- UB	0.86			
	UB3 <- UB	0.93			
	UB4 <- UB	0.71			

5.1 Structural Model Hypothesis Testing

We employed the heterotrait-monotrait ratios (HTMT) to rigorously assess discriminant validity across constructs. These ratios compare correlations between different constructs (heterotrait) to correlations within the same construct (monotrait). Ideally, values below 0.90 indicate robust discriminant validity, while values above this threshold may suggest potential issues of construct similarity. Upon closer examination, several HTMT values raised concerns. Specifically, the HTMT between Behavioral Intention (BI) and Use of Behavior (UB) was 0.964, indicating a high level of similarity between these constructs. Similarly, Effort Expectancy (EE) and Use of Behavior (UB) had an HTMT of 0.932, and Attitude of Others (AO) and Performance Expectancy (PE) showed an HTMT of 0.919, all surpassing the threshold.

To complement these findings, the Fornell-Larcker criterion was also applied to verify discriminant validity. According to this criterion, a construct's Average Variance Extracted (AVE) should exceed its squared correlations with other constructs. Our analysis revealed that each construct's AVE exceeded its squared correlations with other constructs, affirming adequate discriminant validity for the measurement model. However, due to the elevated HTMT values noted earlier, further scrutiny and potential adjustments may be necessary to strengthen the discriminant validity between BI and UB, EE and UB, as well as AO and PE. These findings underscore the importance of meticulous construct delineation and refinement to ensure precise measurement and interpretation in the study.

Table 4. Heterotrait-monotrait ratio (HTMT) - Matrix

	AO	BI	EA	EE	FC	PE	SI	UB	USF
BI	0.870								
EA	0.861	0.720							
EE	0.729	0.809	0.681						
FC	0.863	0.775	0.882	0.627					
PE	**0.919**	0.814	0.768	0.652	0.744				
SI	0.868	0.729	0.816	0.714	0.811	0.837			
UB	0.894	**0.964**	0.685	**0.932**	0.676	0.813	0.683		
USF	0.602	0.539	0.445	0.501	0.338	0.488	0.507	0.490	

Table 5. Fornell-Larcker criterion

	AO	BI	EA	EE	FC	PE	SI	UB	USF
AO	**0.827**								
BI	0.630	**0.923**							
EA	0.650	0.687	**1.000**						
EE	0.528	0.738	0.646	**0.896**					
FC	0.494	0.611	0.719	0.514	**0.835**				
PE	0.687	0.755	0.740	0.600	0.593	**0.913**			
SI	0.610	0.649	0.747	0.647	0.612	0.748	**0.931**		
UB	0.658	0.885	0.666	0.817	0.539	0.752	0.617	**0.862**	
USF	-0.400	-0.475	-0.404	-0.427	-0.248	-0.443	-0.427	-0.451	**0.745**

5.2 Formative Measurement Model Assessment.

Examining the formative measurement model revealed some interesting points. While constructs with VIF (variance inflation factor) values exceeding 5 can be problematic due to multicollinearity, most relationships in this model fall below that threshold. However, a few pairs show moderate levels of collinearity that deserve further attention. Specifically, the EA-to-BI, PE-to-BI, and SI-to-BI relationships have VIF values of 4.915, 4.230, and 4.311, respectively. This suggests these constructs share a moderate amount of variance, which could potentially affect their individual estimates and interpretations. On the other hand, most other pairs, like BI-to-AO, BI-to-USF, and USF-to-UB, have VIF values below 5. This indicates a lower risk of multicollinearity in these relationships. Addressing cases of high VIF values is essential because multicollinearity can produce inaccurate regression coefficient estimates and make the model difficult to understand.

5.2.1 Evaluation of Structural Model

R^2 values of 0.75, 0.50, and 0.25 are considered substantial, moderate, and weak, respectively. However, R^2 values must be interpreted in the context of the model and its complexity. Excessive R^2 values indicate that the model overfits the data (Hair et al., 2021). The predictor factors related to Behavioral Intention (BI) contribute significantly, explaining 79.9% of the variance in BI, indicating strong predictive ability. This implies that the model captures a considerable degree of variation in people's behavioral intentions. The construct Attitude of Others (AO) has a modest level of explanatory power, with an R-square value of 39.7%. Nearly 40% of the variation in people's attitudes toward the beliefs or actions of others can be explained by the path from Behavioral Intention (BI) to Attitude of Others (AO). For the construct Use of Behavior (UB), the R-square value of 80.0% highlights a substantial amount of variability in individuals' actual usage of a particular behavior explained by the specified predictors, primarily influenced by Behavioral Intention (BI). Regarding Unexpected Situational Factor (USF), the R-square value of 22.6% indicates a low level of predictability. The relationship between Unexpected Situational Factor (USF) and Behavioral Intention (BI) helps explain a small amount of the variation in people's perceptions of unforeseen situational circumstances influencing their behavior.

5.2.2 Hypothesis Testing

To assess the importance and reliability of the projected pathways, these statistics are essential. The moderate level of significance shown by the T-statistics of 1.824 and the associated P-value of 0.068 suggests that the association between PE and BI might be significant. Similarly, a moderate level of significance is indicated by the T-statistics of 1.716 and P-value of 0.086 when examining the path from Effort Expectancy (EE) to Behavioral Intention (BI). Significant T-statistics of 5.760, 5.374, and 6.930, respectively, along with P-values of 0.000, demonstrate strong relationships between BI and Attitude of Others (AO), BI and Unanticipated Situational Factor (USF), and BI and Use of Behavior (UB), indicating high relevance. These findings suggest that BI has a statistically significant and robust effect on AO, USF, and UB. In contrast, there is a weak link with non-significant T-statistics (0.256) and a P-value of 0.798 along the path from Unanticipated Situational Factor (USF) to Use of Behavior (UB), as indicated by the original sample value of -0.018. With an initial sample value of 0.163, a T-statistic of 1.524, and a P-value of 0.128, the path from Attitude of Others (AO) to Use of Behavior (UB) shows a weak connection. Specific indirect effects within the model are represented by the provided data. The first scenario involves calculating the indirect relationship between Behavioral Intention (BI) and Use of Behavior (UB) through Attitude of Others (AO). The second scenario examines the Unexpected Situational Factor (USF)-mediated indirect impact of BI on UB. Although indirect influences were observed in both scenarios, the statistical analyses suggest these effects were not statistically significant in the current sample.

5.2.3 Moderation Analysis

Focusing on the relationship between specific moderators, predictors, and behavioral intention (BI), the study explores the effect of experience (EXP) on facilitating conditions (FC) and their impact on behavioral intention (BI).

Table 6. Path Coefficients between variable construct.

Construct	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Result
PE -> BI	**0.512**	**0.499**	**0.281**	**1.824**	**0.068**	**Accepted**
EE -> BI	0.365	0.369	0.213	1.716	0.086	Accepted
SI -> BI	-0.065	0.031	0.346	0.189	0.850	Rejected
FC -> BI	0.107	0.098	0.202	0.530	0.597	Rejected
EA -> BI	0.068	0.024	0.350	0.196	0.845	Rejected
BI -> AO	**0.630**	**0.644**	**0.109**	**5.760**	**0.000**	**Accepted**
BI -> USF	**-0.475**	**-0.498**	**0.088**	**5.374**	**0.000**	**Accepted**
BI -> UB	**0.773**	**0.744**	**0.112**	**6.930**	**0.000**	**Accepted**
USF -> UB	-0.018	-0.033	0.071	0.256	0.798	Rejected
AO -> UB	0.163	0.192	0.107	**1.524**	0.128	Rejected

The interactions examined in the current study did not show statistically significant results in the sample analysis. Specifically, the interaction between Effort Expectancy (EE) and Experience (EXP) on Behavioral Intention (BI) yielded a non-significant path coefficient of -0.164 (T = 0.533, p = 0.594). Similarly, the interaction between Experience (EXP) and Social Influence (SI) on BI resulted in a non-significant path coefficient (T = 0.445, p = 0.656), despite a positive path coefficient of 0.444 suggesting a potential positive moderating effect.

Additionally, the relationship between Performance Expectancy (PE) and BI moderated by Age (AGE) was non-significant, with a path coefficient of 0.245 (T = 0.245, p = 0.807). Similarly, the interaction between Age (AGE) and Social Influence (SI) on BI showed a non-significant path coefficient (T = 1.096, p = 0.273), despite a positive path coefficient of 0.017 indicating a positive moderating effect. Likewise, the interaction between Age (AGE) and Facilitating Conditions (FC) on BI yielded a non-significant path coefficient (T = 0.180, p = 0.807), despite a positive path coefficient suggesting a potential positive moderating effect.

Despite these non-significant interactions, the study underscores the critical role of Behavioral Intention (BI) as an indicator for management to implement strategies aimed at enhancing users' behavioral intention towards digital platforms. The study's validity remains robust despite these limitations within the scope of respondents, focusing on variables that impact adoption models relevant to the workforce dynamics. By concentrating on these specific variables, the study contributes valuable insights into adoption patterns, enriching our understanding of technology adoption models.

The insights gathered from respondents within PT. CKPE, while conforming to minimum sample size requirements typical in social science studies, were tailored to fit the specific context of the technology adoption process within the organization. This approach was informed by various scholarly sources, ensuring alignment with established research methodologies in the field.

6. CONCLUSION

The study's findings underscore the critical roles of Performance Expectancy and Effort Expectancy in shaping users' behavioral intentions to adopt the digital platform for production planning. These factors are pivotal, but the complex mediating influences of others' attitudes and unanticipated situational variables are not significant in this context. Additionally, age and experience do not significantly moderate the connections observed within the UTAUT framework, highlighting the robustness of these elements.

The deployment of a digital platform for production planning will significantly impact PT. CKPE's everyday operations. Performance expectancy, which reflects users' belief in the system's utility and efficiency in improving their work, is a strong and positive influence on their behavioral intention to use the platform. Effort expectancy, or the ease of use of the technology, is another crucial factor favorably influencing users' decision to adopt the platform.

Interestingly, the study finds that the relationship between behavioral intention and other UTAUT characteristics is mediated by the attitudes of others. However, this influence is not statistically significant for the platform adoption in PT. CKPE's daily operations. Similarly, unanticipated situational factors play a mediating role in behavioral intention but do not show statistical significance. The examination of age and experience as potential moderators reveals that neither exerts a significant moderating influence on the UTAUT parameters affecting behavioral intention.

The findings of this research provide insightful information on the variables affecting the platform’s implementation in PT. CKPE. Performance expectancy is a key factor influencing users' behavioral intention to use the platform, indicating that users' intentions are partly determined by their belief in the platform's effectiveness. Similarly, effort expectancy positively influences users' behavioral intentions, with ease of use being a significant determinant. Given the specific circumstances of the study, the findings suggest no substantial moderating influence from either age or experience. This indicates that UTAUT characteristics consistently impact behavioral intention regardless of users' age or level of expertise.

To enhance the platform's performance, it is essential to incorporate features such as intuitive dashboards, a variety of planning and reporting options, informative error events, summarizing pages, reporting tools, mobile access, real-time monitoring, and speedy result evaluation. These enhancements will significantly improve user behavioral intention and usage. Conducting trial operations or pilot testing is recommended to lower users' perceived effort expectations and increase their behavioral intention. Practical trial experiences can help promote positive emotions and higher engagement when using the platform.

Executive management should demonstrate a commitment to fully supporting application development. This includes developing a dedicated team for development, providing essential hardware support, and outlining a clear policy statement. Such support will ensure the platform's successful implementation and adoption. Promoting a positive mindset through regular motivational messaging to all staff members can enhance usage. Aligning all parties involved in the process will foster a cohesive approach to adopting the platform. Addressing unexpected situations continuously by ensuring the application is free of errors or difficult steps will boost constructive utilization behaviors. This proactive approach will help maintain a smooth user experience and encourage consistent platform usage.

Future research should focus on increasing the sample size to strengthen the validity of the research results. A larger participant pool will provide a more comprehensive understanding of the variables influencing the adoption of digital platform for production planning. Providing a detailed description of moderator factors is crucial for obtaining an in-depth understanding of their influence on the observed relationships. Clearly outlining the relationships between pathways, moderating factors, and intervening variables will present a comprehensive understanding of the study design. To improve the accuracy and clarity of the study model, it is important to use clearly specified questions to elucidate the links between latent and manifest variables. Including a wide range of participants will increase the research's inclusiveness and depth, considering variables like respondent capabilities, age, and gender. Adding interview sessions with key players will increase the possibility of better answers to the problems related to the platform adoption. These interviews will provide valuable insights and help refine the strategies for successful implementation. By addressing these recommendations, future research can provide a more detailed and inclusive understanding of the factors influencing the adoption of digital production platforms, ultimately contributing to more effective implementation strategies in similar organizational contexts.

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APPENDIX 1

Table A. Questionnaire

No	Construct	Question	Ref.
1	Performance Expectancy	The use of this digital production platform will help you optimize the production process.PE1	[8]; [12]; [2]
2		The digital production platform will be very useful in improving production efficiency and quality.PE2	
3		This digital production platform will enhance production outcomes and overall resource utilization. PE3	
4		The use of this digital production platform helps you achieve production goals more quickly.PE4	
5	Effort Expectancy	You can learn and use this platform effectively.EE1	[8]; [12]; [2]
6		Interacting with this platform is clear and engaging for you.EE2	
7		You feel comfortable using this platform in daily activities.EE3	
8	Social Influence	The adoption of this digital production platform is expected to be supported by colleagues and superiors.SI1	[8]; [12]; [2]
9		My colleagues/superiors suggested that I use this digital production platform.SI2	
10		The support of all relevant parties is crucial in the adoption of this digital production platform.SI3	
11	Facilitating Conditions	I have sufficient resources and infrastructure to implement this digital production platform.FC1	[8]; [12]; [2]
12		Lack of technical expertise may be a constraint in adopting this digital production platform.FC2	
13		The intuitive interface and user-friendly design of this digital production platform make it easy for anyone to learn.FC3	
14		The availability of specialized technical support for this platform ensures smooth implementation and ongoing assistance.FC4	
15	Evaluation of Alternative	My colleagues and superiors consider this digital production platform superior to other options.EA1	[12]
16		Management supports the use of this digital production platform for production needs.EA2	
17		Your colleagues and superiors evaluate this digital production platform in line with the company's goals.EA3	
18		My friends believe that this digital production platform can enhance collaboration within the team.EA4	
19	Attitudes of Others	In general, your colleagues and superiors respond positively to the adoption of this digital production platform.AO1	[5]

20		There are concerns from other teams or departments regarding the implementation of this digital production platform.AO2	
21		You have received positive recommendations for this digital production platform from colleagues outside your current work area.AO3	
22		Management provides adequate support and investment for the implementation of this production platform.AO4	
23	Perceived risk - Psychological risk	I believe that this platform is reliable, reducing my concerns about risks in production planning.PR1	[5]
24		I am worried that this platform may malfunction and cause accidents or production errors.PR2	
25		I feel anxious about relying on the platform for challenging tasks.PR3	
26		I feel insecure using this platform if there are technical errors or issues.PR4	
27	Unanticipated Situational Factor- Time risk	The digital production platform is complex; it takes a long time to learn.TR1	[5]
28		In the transition period of this digital production platform, production may be disrupted and delayed.TR2	
29		The digital production platform is highly dependent on technology; there is a fear of breakdowns causing production delays.TR3	
30		You are unsure if this digital production platform can save time in planning and reporting production tasks.TR4	
31	Behavioural Intention	This new digital production platform is very beneficial.BI1	[12]; [1]; [15];
32		If this digital production platform is available, I will use it.BI2	
33		You strongly encourage others to use this digital production platform.BI3	
34	Use Behaviour	You intend to continue using this digital production platform in the future.UB1	[12]
35		You will always strive to use this platform in your daily work.UB2	
36		You will highly recommend this platform to others.UB3	
37		You depend on this platform for planning and reporting production tasks.UB4	