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TECHNOLOGY ACCEPTANCE MODEL (TAM) FOR PHARMACEUTICAL MARKETING EXECUTIVES: VALIDATION AND IMPLICATIONS FOR HUMAN RESOURCE MANAGEMENT

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Abstract: The technology acceptance model (TAM) is a popular measure of user adoption and acceptance of technology. The pharmaceutical marketing industry has largely incorporated technology-based applications to enhance operational efficiency, effectiveness, and client engagement in the past decade. No study has explored user acceptance by pharmaceutical executives in the context of technology's impact on performance. The study aims to explore the relationship between perceived ease of use (PEOU), perceived usefulness (PU), and behavioral intention (BIU) in the context of the perceived impact of technology on performance (TechIMP). Hypotheses were tested using factor-based structural equation modeling. A random sample of 282 marketing executives was drawn from pharmaceutical companies in Nigeria using an online questionnaire. The developed model provided acceptable measures of fit and validity. Significant positive relationships exist between PEOU, PU, and BIU, explaining 58% of the variance in TechIMP. PEOU had a stronger impact on BIU compared to PU. BIU was a significant link between PEOU and PU to TechIMP. Multigroup analysis showed key differences between male and female executives. The study adds to the existing literature by extending TAM to include TechIMP. Managers should enhance positive user perception and acceptance by engaging in simulated training before introducing new technology and ensuring flexibility of technology use.

Keywords: Technology Acceptance Model, Human Resource Management, Pharmaceutical Marketing, Technology Impact, Performance

CITATION

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INTRODUCTION

The pharmaceutical marketing industry has incorporated technology-based apps to improve field-based employees' internal operations, customer engagement, and performance measures in the past decade. The impact of technology-guided operations has significantly reduced transaction costs and interactions between persons to more parsimonious, efficient, and effective business transaction and customer management systems. In prevalent use are mobile payment apps, team mobility apps, delivery times apps, e-detailing, and real-time performance monitoring systems.

The rapid shift to more technology-based operations is partly adduced to the changes in operations of pharmaceutical executives due to the challenges of the COVID-19 pandemic and limited resources due to global economic downturn (Oamen, 2021; Kwak and Chang, 2016; Kwak and Chang, 2022; Kim and Chang, 2022). Hence, optimizing client engagement and business profitability has led to a paradigm shift from face-to-face or physical contact to more emphasis on the remote and virtual interactions (Molloy et al., 2002). The Technology Acceptance Model (TAM) is one of the foremost and most extensively applied social psychology theories developed by Davis and his colleagues (Davis et al., 1989; Davis, 1989) as an extension of the theory of reasoned action (TRA) proposed by Fishbein and Azjen (1975). TAM is widely applied as an efficient and robust framework for predicting, assessing, and explaining user acceptance and adoption of technology in many disciplines. They include information systems (Diop et al., 2019), marketing (Ahn et al., 2004), education (Su and Li, 2021), and e-learning (Bhattacharyya et al., 2020). Despite the availability of technology for improved marketing operations, it is necessary to assess the psychometric properties of the model (TAM) and user acceptance among the pharmaceutical workforce involved in technology utilization for optimal job performance.

Technology and information systems for managing sales operations have evolved over the past decades. The transition from the conventional direct-to-colleague and direct-to-client approach to technology-aided processes has become increasingly commonplace (Kwak and Chang, 2016). This rapid shift has remodeled communication and efficiency of the operations with colleagues and clients, as evidenced by the common use of trade monitoring, geographical monitoring of work teams, and team management applications (Kwak and Chang, 2016).

However, in Nigeria and perhaps globally, user acceptability by pharmaceutical executives has not been empirically investigated in the context of technology's impact on the performance (TechIMP). It is substantiated by the lack of empirical evidence to support user acceptance in the pharmaceutical marketing industry. Therefore, it is imperative to assess TAM among pharmaceutical executives in Nigeria, considering that the country arguably has the largest pharmaceutical market in Africa (McKinsey, 2017).

The TAM aligns with the theory of reasoned action in which the behavioral intentions (BIU) to exhibit a desired action or behavior are influenced by attitudes and perceptions such as perceived ease of use (PEOU) and the perceived usefulness (PU). These attitudes invariably impact actual system use, impacting TechIMP (Fishbein and Azjen, 1975). Hence, it is important to validate the applicability of TAM among pharmaceutical executives and explore the structural relationships between the key elements of TAM- PEOU, PU, BIU) and TechIMP.

To the best of the author's knowledge, this is the first study to assess the acceptance and usability of TAM among pharmaceutical executives. The study's relevance is based on the imperative to provide a validated tool that strategic and human resource managers can use to evaluate the impact of technology adoption domains among employees in the pharmaceutical industry. The study's objectives are: 1) assess the psychometric properties of the TAM research tool, 2) assess user adoption of technology using a structural model to estimate effects, and 3) explore possible path differences based on gender, company type, and work role.

LITERATURE REVIEW

The technology acceptance model (TAM) advanced by Davis (1989; 2023) is a widely utilized measure of user adoption, prediction, and acceptance of technology from the information systems discipline (Davis, 1989; Davis et al., 2023). Numerous studies have been done in many disciplines using the lens of TAM, such as health informatics (Onyeachu and Clarke, 2022), health administration (Nguyen et al., 2020; AlQudah et al., 2021), public health (Pertiwi et al., 2022), education (Alharbi and Drew, 2014), governance (Suki and Ramayah, 2010), and technology management (Chuah et al., 2016).

Fishbein and Azjen (1975) asserted that an individual's behavior is influenced by the attitudes, which are consequences of intentions that were impacted by the external factors or belief systems. However, Davis opined that belief systems (exemplified by PU and PEOU) influence the intention to exhibit certain behaviors (BIU), which invariably influences the actual use of a given technological system or tool. In the more parsimonious TAM advanced by Davis, the key elements were PEOU, PU, BI, and actual system use (Davis et al., 1989).

Technology-based platforms in pharmaceutical marketing have evolved over the years with the increased use of e-business platforms in marketing (Lerer, 2002; Greene and Kesselheim, 2010) and social media in consumer advertising (Liang and Mackey, 2011). E-detailing and feedback platforms for drug detailing (Kim and Chang, 2022). In the context of pharmaceutical marketing, Kim and Chang (2022) explored the user acceptance of TAM concerning e-detailing technology by medical representatives (Kim and Chang, 2022). The study showed that those with the pro-innovative mindsets were more aligned to adopt this communication mode with their clients (Kim and Chang, 2022). Likewise, Jaradat and Smadi (2013) affirmed that PEOU had a dominant effect on BIU for mobile platforms in healthcare provision (Jaradat and Smadi, 2013). However, no study has been done to assess the psychometric characteristics of the model among pharmaceutical executives involved in the marketing of pharmaceutical services and products.

HYPOTHESIS DEVELOPMENT

Perceived ease of use (PEOU) refers to the ease with which an individual uses a particular technology. As a consequence, any technology used with high PEOU would impact PU. PEOU expresses the convenience, effort, understanding, and flexibility of using a particular technology (Davis, 1989; Davis et al., 1989). In TAM, positive PEOU influences BIU and PU (Venkatesh, 2000; Alharbi and Drew, 2014). Some studies have shown that PEOU influenced PU and BIU among pharmaceutical executives who deploy e-detailing devices in physician interactions (Kim and Chang, 2022). However, it is relevant to assess the impact of the PEOU on the performance outcomes of pharmaceutical executives. Therefore, it is postulated that PEOU would have a direct effect on pharmaceutical executives' BIU, PU, and TechIMP.

Perceived usefulness (PU) implies that the technology use has some form of positive impact, relevance, or importance on the performance of the individual. PU covers the technology users' perception of how it positively or negatively affects their job operations and, consequently, performance (Davis, 1989, 1993). Users are more likely to adopt a technology that has the potential for highly positive benefits to their core activities than those that only contribute to non-critical aspects of their job (Venkatesh, 2000; Davis et al., 2023). However, the role of PU as a key factor in the TAM requires investigation in the context of the pharmaceutical marketing industry.

Behavioral intention (BIU) refers to an individual's positive or negative inclination or tendency to use and adopt a particular technology. BIU suggests that a satisfied user would most likely continue to use, recommend, or have positive feelings if they have positive or high levels of PU and PEOU about the technology (Davis, 1989, 1993). A study by Kwak and Chang (2016) assessing BIU concerning the use of e-detailing devices in marketing activities by pharmaceutical executives revealed that PU more significantly influenced BIU than PEOU (Kwak and Chang, 2016). In the context of this study, the impact of PU and PEOU on BIU among pharmaceutical marketing executives was explored

Perceived Impact of Technology on Performance (TechIMP) refers to the impact of technology on the work domains of pharmaceutical executives. TechIMP is a critical measure to evaluate how much impact technology has on enhancing work performance in pharmaceutical marketing companies. TechIMP can be measured using the following indicators: improvement in efficiency and cost management, enhanced sales output, profitability, time savings, reduced paperwork, and enhanced communication with clients and colleagues (Shabaninejad et al., 2014). Other key performance indicators include enhanced financial accountability capacity, limited physical meeting times, facilitator of sales operations, and cost efficiency (Oamen, 2021). Therefore, the direct and indirect effects of BIU, PEOU, and PU on the benefits of TechIMP, as perceived by pharmaceutical executives, were investigated.

Multigroup Analysis of hypothesized structural relationships provides a basis for comparing distinct groups in a sample. It provides evidence of the absence or presence of statistically significant differences between subgroups in a given population (Oamen and Ihekoronye, 2022; Sarstedt et al., 2011). Before evaluating for differences between groups, it is important to ensure that the subgroups are invariant, in which case, differences should not be attributed to instrumentation error or bias. In other words, it is not due to measurement model differences across the groups. Hence, measurement invariance testing is a precondition before comparing groups (Henseler et al., 2016; Oamen et al., 2022).

Study Hypotheses

The following hypotheses of the study were divided into Model fit and quality, Direct effects, Mediation effects, and Multigroup Analysis effects, as outlined in the figure 1.

Model Fit and Quality

H1 : There is an adequate fit of the hypothesized model to the data.

H2 : There is construct validity (convergent and discriminant) of the model.

Direct Effects

H3 : PU has a positively significant influence on BIU to use of technology.

H4 : PU has a positively significant influence on TechIMP of pharmaceutical executives.

H5 : PEOU has a positive influence on PU.

H6 : PEOU has a positively significant influence on BIU.

H7 : PEOU has a positively significant influence on TechIMP of pharmaceutical executives.

H8 : BIU has a positively significant influence on the TechIMP of pharmaceutical executives.

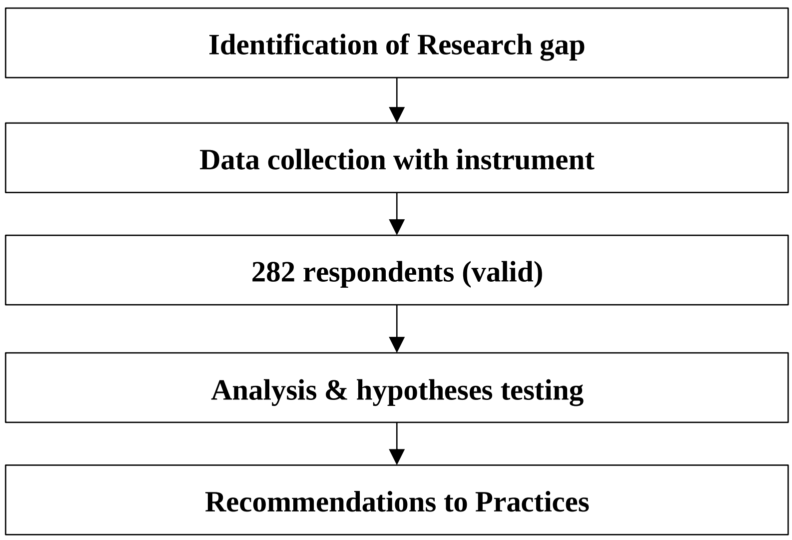
Indirect Effects (Mediation)

H9 : PU has a positively significant mediating effect on the relationship between PEOU and BIU.

H10 : BIU positively mediates the relationship between PEOU and TechIMP.

H11 : BIU has a significantly positive mediating effect on the relationship between PU and TechImp.

H12: PU and BIU positively mediate the relationship between PEOU and TechIMP (serial mediation).



Source: Author's computation (2023)

Figure 1. Research Framework

Multigroup Effects

H13 : There is a significant difference in perception of pharmaceutical executives based on gender, company type, and work role (multigroup analysis).

METHOD

The quantitative cross-sectional study involved the online administration of structured questionnaires to 282 randomly selected pharmaceutical executives from 25 multinational and indigenous pharmaceutical companies in Nigeria. Sample size calculation was based on the inverse square root method with an estimated effect size of 0.2 at a p-value set at 0.01 to give a minimum sample size of 251 suitable for a structural model (Kock and Hadaya, 2018). The descriptive statistics, exploratory factor analysis (EFA), and common method bias assessment were done using the statistical package for the social sciences (SPSS). Factors (constructs) and their measurement indicator loadings were computed using the maximum likelihood extraction method with Promax rotation. Measurement items for factors were included if they had loadings less than or equal to 0.3, as Blunch (2016) recommended. The measurement invariance test, path analysis, and multigroup analysis were analyzed using structural equation modeling (SEM) in WarpPLS (Kock, 2022). The informed consent was obtained from respondents before filling out questionnaires.

Measurement of Variables

The variables used in the study were measured by indicator items using the Likert scale. PU was measured on a 5-point Likert scale of 1 to 5 where 1 (strongly disagree), 2 (disagree), 3 (neither agree nor disagree), 4 (agree), and 5 (strongly agree). PEOU was measured on a 4-point Likert scale where 1 (rarely), 2 (sometimes), 3 (often), and 4 (always). BIU was measured on a 5-point Likert scale where 1 (never), 2 (rarely), 3 (sometimes), 4 (often), and 5 (always). Technology's impact on job performance (TechIMP) was measured with a 4-point Likert scale of 1 (strongly disagree), 2 (disagree), 3 (agree), and 4 (strongly disagree).

Common Method Bias

Common method bias (CMB) was measured using Harman's single-factor method in the factor analysis algorithm in SPSS to identify the presence or absence of CMB (Kock, 2021: Jordan and Troth, 2020). The presence of CMB implies that the trend of the questions asked respondents unduly tilted in the same direction, thereby introducing bias and potentially unreliable responses. A variance of 46.54% accounted for the variability for a single factor, which falls below the threshold value of 50% (Jordan and Troth, 2020; Kock, 2021).

Measurement Invariance of Hypothesized Paths

Measurement invariance tests for multigroup SEM models ensure that differences between groups are not due to instrument error/bias or failure of equivalence in understanding the research questions by respondents but due to actual empirical differences (Oamen et al., 2022). Oamen et al. (2022) argued that reporting measurement invariance in behavioral research is essential to ensure equivalence of the understanding of research questions among groups.

Table 1. Operational Definition of Variables

Variables	Definition	References
Perceived Usefulness (PU)	the perception of the technology users as to how it positively or negatively affects their job operations and, consequently, performance	Davis, 1989; Davis et al., 1989; Venkatesh, 2000
Behavioral Intention to Use (BIU)	refers to an individual's positive or negative inclination or tendency to use and adopt a particular technology	Davis, 1989; Davis, 1993
Perceived Technology Impact on Performance (TechIMP)	refers to the impact of technology on the work domains of the pharmaceutical executives	Shabaninejad et al., 2014; Oamen, 2021

Source: Author's computation (2023)

Measurement Invariance is a recommended prerequisite before analyzing a structural model's path coefficients and conducting a multigroup analysis in research (Henseler et al., 2016; Sarstedt et al., 2011). To test for invariance in WarpPLS, an algorithm using the Satterthwaite analysis method for establishing the presence or absence of invariance between groups is available (Kock, 2022; Oamen, 2023). A statistically insignificant difference in the indicator loadings of the constructs (absolute loading difference) between the two groups confirms invariance.

Table 2. Measurement Invariance based on Gender, Type of Company, and Work Role

CONSTRUCTS	Gender		Company Type		Work role	
Indicators	**path diff.**	**t-value**	**path diff.**	**t-value**	**path diff.**	**t-value**
Perceived Usefulness (PU)						
PU1	0.080	0.759	0.010	0.100	0.026	0.235
PU2	0.017	0.158	0.050	0.594	0.063	0.565
PU3	0.021	0.194	0.001	0.010	0.012	0.111
PU4	0.023	0.220	0.029	0.292	0.083	0.747
PU5	0.047	0.444	0.004	0.044	0.018	0.167
PU6	0.024	0.231	0.038	0.383	0.033	0.298
Perceived Ease of Use (PEOU)						
PEOU1	0.021	0.184	0.144	1.345	0.068	0.581
PEOU2	0.111	1.032	0.066	0.649	0.008	0.070
PEOU3	0.074	0.695	0.034	0.341	0.049	0.435
PEOU4	0.036	0.339	0.097	0.967	0.052	0.465
PEOU5	0.071	0.660	0.075	0.745	0.096	0.842
PEOU6	0.060	0.550	0.014	0.136	0.038	0.328
Behavioral Intention to Use (BIU)						
BIU1	0.116	1.097	0.054	0.542	0.017	0.155
BIU2	0.009	0.083	0.071	0.720	0.020	0.179
BIU3	0.116	1.099	0.027	0.273	0.080	0.739
BIU4	0.029	0.277	0.028	0.284	0.069	0.625
BIU5	0.020	0.185	0.090	0.885	0.154	1.329
Technology Impact on Performance (TechIMP)						
TIP1	0.005	0.049	0.053	0.520	0.002	0.018
TIP2	0.018	0.166	0.040	0.394	0.052	0.468
TIP3	0.082	0.744	0.063	0.625	0.150	1.293
TIP4	0.021	0.188	0.073	0.702	0.152	1.270
TIP5	0.001	0.011	0.020	0.197	0.033	0.294
TIP6	0.006	0.057	0.010	0.095	0.009	0.077
TIP7	0.062	0.567	0.057	0.560	0.058	0.523
TIP8	0.044	0.406	0.032	0.318	0.001	0.010
TIP9	0.012	0.111	0.007	0.071	0.002	0.019

Note: *t-value<t-critical, p>0.05, non-significant differences depict invariance
Source: Author's computation (2023)

Table 2 shows the computation of measurement invariance of the hypothesized model. It showed that based on gender, type of company, and functional work role. There is a non-significant statistical difference between the groups regarding the measured constructs (that calculated t values are less than 1.96, at a 5% significance level). In other words, within the groups- gender (males and females), company type (multinational vs. indigenous), and work role (field executives vs. managers), there were no differences in how they understood or perceived the various questions (measurement items) in the research instrument. This procedure is highly recommended for social and behavioral research involving distinct groups or categories (Oamen et al., 2022).

RESULTS

Table 3 shows the majority of respondents are male (72.7%), and 27.3% are female, with approximately equal distribution as single and married. Most respondents are between 20 and 40 years old (n=253, 89.7%), while 10.3% are 41 years and above. Multinational companies had 118 (41.8%), while more respondents work with indigenous companies. Based on work roles, 41.4% are managers, while most (n=164, 58.2%) are field sales and marketing executives. In terms of years of work experience in the pharmaceutical marketing industry, a minority (n=40, 14.2%) had more than 10 years, 213 (75.6%) had between 1 to 10 years, and the least were those with less than a year of work experience in the industry (n=29,10.3%).

Table 3. Demographic Characteristics of Participants

Attributes		Frequency (n)	Percentage (%)
Gender			
	Female	77	27.3
	Male	205	72.7
Marital status			
	Married	139	49.5
	Single	143	50.7
Age (yrs.)			
	20-25	19	6.7
	26-30	100	35.5
	31-40	134	47.5
	41-49	27	9.6
	greater than 50	2	0.7
Qualification			
	HND	13	4.6
	BSc	165	58.5
	BPharm/PharmD	104	36.9
Company Type			
	Indigenous	164	58.2
	Multinational	118	41.8
Work Role			
	Field executives	216	76.6
	Manager	66	23.4

Attributes	Frequency (n)	Percentage (%)
Yrs. of Industry experience		
Less than 1 yr.	29	10.3
1-5 yrs	153	54.3
6-10 yrs.	60	21.3
11-15 yrs.	29	10.3
Greater than 15 yrs.	11	3.9
Total	**282**	**100**

Source: Author's computation (2023)

Table 4. Exploratory Factor Analysis of Measurement Items

CONSTRUCTS	Description	Factor loading
Perceived Usefulness (PU)		
PU1	Technology helps me perform tasks faster	0.781
PU2	Technology enables me to make timely decisions	0.724
PU3	Technology improves my work performance	0.835
PU4	Technology increases my productivity	0.843
PU5	Technology makes my work processes easier to execute	0.874
PU6	I find the technology useful in my job	0.919
Perceived Ease of Use (PEOU)		
PEOU1	Technology does not require much mental effort to execute	0.483
PEOU2	Technology is easy to learn and operate	0.818
PEOU3	Technology is easy to understand or comprehend	0.946
PEOU4	Technology is easy to use	0.871
PEOU5	Technology is flexible to interact or work with	0.517
PEOU6	Technology enables me to achieve my key goals easily	0.371
Behavioral Intention to Use (BIU)		
BI1	I will use technology as long as it is available	0.878
BI2	I will recommend technology to colleagues to my colleagues	0.708
BI3	I think it is relevant to my work	0.752
BI4	I will most likely use technology if it is available	0.992
BI5	Technology is the best work tool for now	0.433
Technology Impact on Performance (TechIMP)		
TIP1	Technology use has improved my performance significantly	0.647
TIP2	Technology use has improved my inventory management skills	0.801
TIP3	Technology use has improved my selling skills	0.728
TIP4	Technology use has reduced my paperwork significantly	0.577
TIP5	Technology use has improved my communication with colleagues at work	0.793
TIP6	Technology has improved information sharing with clients and colleagues	0.793
TIP7	Technology use has enhanced my financial accountability at work	0.763
TIP8	Technology use has reduced physical meeting time significantly	0.744
TIP9	Technology use has reduced my cost of doing business	0.803

Source: Author's computation (2023)

As shown in Table 4, the exploratory factor analysis of the measurement items or indicators revealed that all indicators had loadings above the benchmark of 0.3 (Blunch, 2016). Hence, the data fully represents the constructs and is useful for further analysis.

Model Fit and Quality Measures

The measurement model had acceptable model fit characteristics: standardized root mean squared residual (SRMR) = 0.082 (cutoff = 0.1), standardized mean absolute residual (SMAR) = 0.064 (acceptable if ≤0.1), average full collinearity variance inflation factor (AFCVIF) = 2.365 (acceptable if ≤5, ideally ≤3.3). The coefficient of determination (R2) for each of the endogenous variables exceeded the limit of 10% raised by Falk and Miller (1992) for endogenous constructs, with 26.1% for PU, 61.2% for BIU, and 58.2% for TechIMP, respectively. Therefore, the explanatory or exogenous variables largely explain the endogenous or dependent variables or constructs. Hence, hypothesis H1 is satisfied, meaning that the model fits the data and represents a worldview.

Table 5. Assessment of Measurement Model (Internal Reliability and Collinearity Measure)

CONSTRUCTS	Factor loading	FCVIF	CR	Cronbach	AVE
Perceived Usefulness (PU)		2.399	0.938	0.938	0.717
PU1	0.835				
PU2	0.798				
PU3	0.860				
PU4	0.866				
PU5	0.852				
PU6	0.868				
Perceived Ease of Use (PEOU)		1.936	0.876	0.867	0.545
PEOU1	0.548				
PEOU2	0.759				
PEOU3	0.796				
PEOU4	0.816				
PEOU5	0.768				
PEOU6	0.709				
Behavioral Intention to Use (BIU)		2.734	0.907	0.906	0.662
BIU1	0.804				
BIU2	0.850				
BIU3	0.813				
BIU4	0.839				
BIU5	0.760				
Technology Impact on Performance (TechIMP)		2.392	0.917	0.917	0.552
TIP1	0.742				
TIP2	0.779				
TIP3	0.755				
TIP4	0.678				
TIP5	0.759				
TIP6	0.758				
TIP7	0.717				
TIP8	0.733				
TIP9	0.764				

*FCVIF=full collinearity variance inflation factor, CR-composite reliability, AVE-average variance extracted
Source: Author's computation (2023)

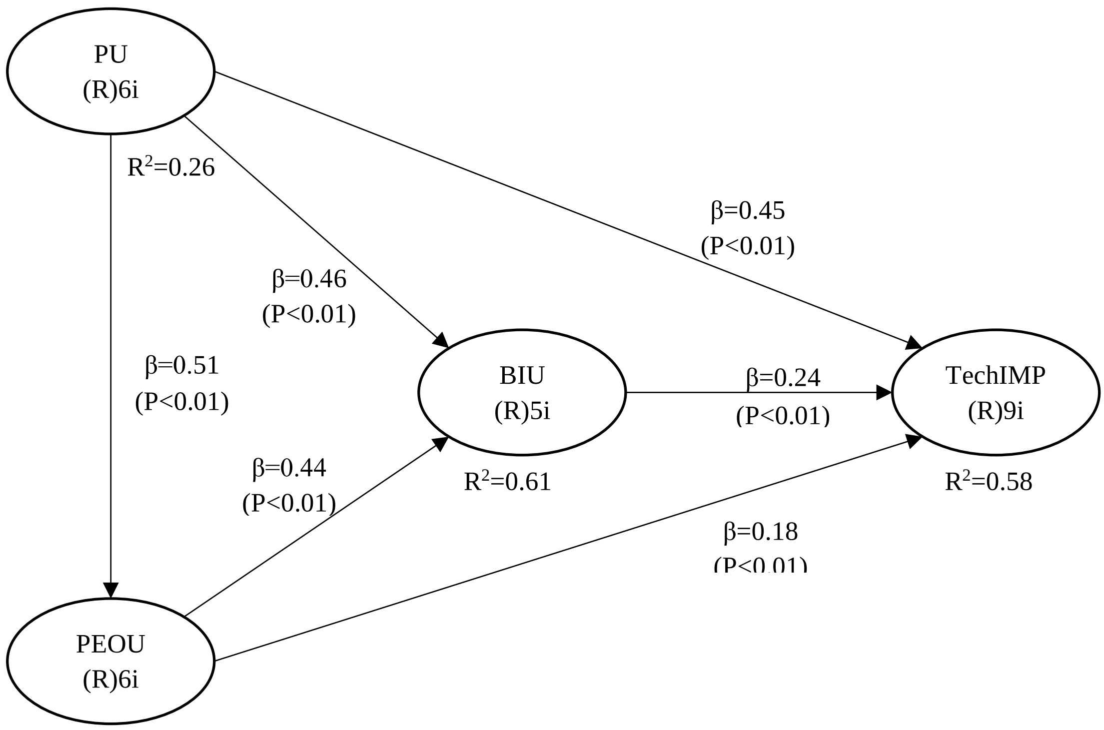
Table 5 shows the confirmatory factor analysis results with factor loadings of the indicators and constructs above the recommended value of 0.5 (Hair et al., 2010). The multicollinearity of the constructs was not present, as the full collinearity variance inflation factor (FCVIF) was below 3.3. Thus, the constructs are not unduly correlated with each other. Convergent validity measures of the model, such as CR and AVE, were satisfactory, with values above cutoffs of 0.7 and 0.5, respectively (Henseler et al., 2015).

As shown in Table 6, the distinctness and separability of each construct from the other were examined using Fornell and Larcker and Heterotrait Monotrait criteria (Henseler et al., 2015). For the Fornell and Larcker criterion, the square root of the AVEs of the constructs (in bold along the diagonal) is higher than the intercorrelations between the constructs. In HTMT, the study constructs PU, PEOU, BIU, and TechIMP had values less than the strict benchmark value of 0.85 (Henseler et al., 2015). Therefore, based on the model achieving construct validity measures (convergent and discriminant), hypothesis H2 was supported.

Table 6. Discriminant Validity Measures

	Fornell and Larcker criterion				**Heterotrait Monotrait criterion**			
Constructs	**PU**	**PEOU**	**BIU**	**TechImp**	**PU**	**PEOU**	**BIU**	**TechIMP**
PU	**0.847**							
PEOU	0.514	**0.738**			0.519			
BIU	0.687	0.677	**0.814**		0.692	0.690		
TechIMP	0.708	0.572	0.671	**0.743**	0.710	0.584	0.674	

Note. Heterotrait Monotrait=HTMT
Source: Author's computation (2023)



Source: Author's computation from WarpPLS output (2023)

Figure 2. Structural Model

As depicted in Figure 2, the structural model's coefficient of determination (R^2: R-squared) was 26%, 61%, and 58% for PU, BIU, and the main dependent variable-TechIMP respectively. These values are within the baseline of ≥0.25 to ≥0.75 (below 25% is weak, greater than 50% is moderate, and above 75% is strong), according to Hair et al. (2021); hence, the model has high predictability or explanatory power of the independent variables (amount of variance in the dependent variable explained by the independent variables).

Table 7 showed the results of path analysis with positive and significant relationships existing in all the hypothesized paths (H3, H4, H5, H6, H7, and H8) at p<0.001 and with small to moderate effect sizes. Table 8 showed the outcome of mediation analysis with significant mediation effects of PU and BIU at p<0.01. A statistically significant serial moderation effect of PU and BIU was found in the relationship between PEOU and TechImp at p<0.05. Therefore, the hypotheses (H9, H10, H11, and H12) were generally supported. However, the mediating effect is partial (partial mediation) because the direct effects of PEOU and PU on the main dependent variable (TechIMP) were positive and significant, as shown in the path analysis (Table 7). Hence, the mediating variable provided a critical contribution to explaining how the independent variable exerts its effects on the dependent variable (Moqbel et al., 2020).

Table 7. Path Analysis of the Structural Model (Direct Effects)

Path	coefficient (β)	t-value	*p*-value	Cohen's (f^2)	Hypothesis (H)	Inference
PU-> BIU	0.462	8.353	0.001	0.317	**H_3**: supported	moderate effect
PU -> TechIMP	0.451	8.157	0.001	0.320	**H_4**: supported	moderate effect
PEOU -> PU	0.514	9.375	0.001	0.264	**H_5**: supported	moderate effect
PEOU -> BIU	0.440	7.927	0.001	0.297	**H_6**: supported	moderate effect
PEOU -> TechIMP	0.178	3.068	0.001	0.102	**H_7**: supported	small effect
BIU -> TechIMP	0.240	4.190	0.001	0.161	**H_8**: supported	moderate effect

Source: Author's computation (2023)

Table 8. Mediation Analysis of Model (Indirect Effects)

Path	coefficient (β)	p-value	Cohen's (f^2)	Hypothesis (H)	mediation
PEOU-->PU--->BIU	0.237	0.001	0.160	**H_9**: supported	PU
PEOU-->BIU--->TechIMP	0.111	0.004	0.078	**H_{10}**: supported	BIU
PU-->BIU--->TechIMP	0.337	0.001	0.193	**H_{11}**: supported	BIU
PEOU-->PU--->BIU--->TechIMP	0.057	0.048	0.033	**H_{12}:** supported	PU and BIU

Source: Author's computation (2023)

Table 9. Multigroup Analysis of Structural Relationships in Model

Path	Male	Female	Absolute diff	*p*-value	Inference
PU-> BIU	0.527	0.326	0.201	0.049*	stronger in males
PU -> TechIMP	0.440	0.441	0.001	0.498	no difference
PEOU -> PU	0.497	0.533	0.036	0.379	no difference
PEOU -> BIU	0.367	0.579	0.212	0.033*	stronger in females
PEOU -> TechIMP	0.114	0.405	0.291	0.008**	stronger in females
BIU -> TechIMP	0.300	0.057	0.243	0.031*	stronger in males

Note. *p<0.05, **p<0.01
Source: Author's computation (2023)

Table 9 shows the comparative difference in perception based on gender; males had stronger effects in the relationships between PU and BIU and the direct relationship between BIU and TechIMP. Conversely, females had stronger effects on the relationships between PEOU and BIU. As well as PEOU and TechIMP. It is worthy of note that prior multigroup analysis using company type and work role revealed no statistically significant difference between groups.

DISCUSSION

The study addressed the validation of TAM in the context of TechIMP among pharmaceutical executives. The article expands existing literature by providing more insight into the influence of the technology acceptance on performance. It is relevant because of the need to maximize technology to the fullest in marketing pharmaceutical products and services at the lowest possible cost to pharmaceutical marketing companies.

Hypotheses Testing

In line with the study's main objective, the measurement and structural models showed acceptable psychometric attributes (as shown in Tables 4, 5, and 6), which validate the adapted model (TAM) for use in assessing technology use and acceptance among pharmaceutical executives. Hence, hypotheses 1 and 2 (H1, H2) were supported. From a practical perspective, the study provided additional insights into the comparative relevance of PEOU and PU on TechIMP. As shown by the results in Table 7, PEOU had more influence on BIU than PU. It implies that the more user-friendly, flexible, and adaptable an introduced technology intervention is, the more impact or positive influence it has on the intention of the person to use it, and invariably impacts performance. In order words, it exerts a significant effect on the desire to perform or exhibit a specific behavior. This finding is corroborated by Kwak and Chang (2016), who asserted that enhanced PEOU and PU have a positive impact on BIU among pharmaceutical representatives. Thus, empirical evidence from the structural model supported hypotheses 3 to 8 (H3 to H8).

The study empirically tested the mediating role of PU and BIU in explaining the relationship between PEOU and TechIMP, as shown in Table 8. The significant mediation effects imply that the usefulness and intention to use technology are critical links that enable pharmaceutical executives to translate their PEOU to actual performance. Therefore, hypotheses H9, H10, H11, and H12 were supported respectively. Therefore, pharmaceutical executives are more likely to have enhanced performance due to technology use when their sense of PU and BIU is strengthened or increased. It affirms that appropriate management measures that increase awareness of the usefulness of any adopted technology, enhanced usage flexibility, and enhanced willingness to adopt technology should be encouraged.

The study explored the differences using multigroup analysis based on gender, company type, and work role, as shown in Table 9, to test hypotheses (H13) due to potential demographic differences inherent in the study population. Prior analysis showed equivalence or parity in path coefficient (statistically non-significance) in company type and work role. It implies that they do not constitute any difference among pharmaceutical executives. In the same vein, it means that executives in indigenous or multinational companies and those in the field or management cadre do not seem to differ in perception in terms of technology acceptance. Based on the multigroup analysis, gender differences exist in pharmaceutical executives' perception of technology acceptance, thereby supporting the hypothesis (H13). Hence, the stronger influence of PU on BIU in males compared to females implies that male counterparts tend to be more task-oriented in using electronic-based technology than females. This outcome is similar to the findings of Okazaki and Santos (2012), who did a comparative analysis of technology acceptance between male and female faculty members (Okazaki and Santos, 2012). Also, this finding aligns with outcomes of studies by Ong and Lai (2006) and Goswami and Dutta (2016) that showed a higher proclivity of males to adopt technology that supports performing tasks effectively compared to females (Ong and Lai, 2006; Goswami and Dutta, 2016). However, Islam et al. (2011) highlighted that females experience operational challenges with e-learning technology compared to males in a learning institution in Malaysia. Therefore, in this study, gender differences in the technology user acceptance have been shown to exist among pharmaceutical executives, as established in the literature concerning team collaboration (Shen et al., 2010).

Furthermore, the path from PEOU to BIU showed higher importance to female executives compared to males. It suggests that females have more favorable perceptions of the likely ease or user-friendliness of technology applications, influencing their intention to apply technology. This is corroborated by empirical research findings by Amin et al. (2015), who asserted that females have a higher tendency to use technology based on the ease with which a given technology can be applied (PEOU) compared to men (Amin et al., 2015).

IMPLICATIONS

The study findings show that performance management has clear links with user acceptance and use of technology in the pursuance of organizational objectives or goals. The study's findings can be extended to include marketing personnel from the other sectors where performance management is a critical outcome measure, as seen in financial institutions and sales organizations.

The sales and marketing organizations must perform needs assessments of their operations and employees to identify the technology need areas requiring training and development. It would strengthen the mechanism or linking of intention to adopt and use any technology. In the same vein, management can influence positive organization-friendly perceptions and invariably elicit desired behaviors from employees when educational programs and workshops on the benefits of using the technology are routinely promoted.

Therefore, performance management linked to employees' technology should be an important agenda for strategic managers, particularly in developing the countries. This approach should be adopted as a matter of policy, including capacity development initiatives to explore the relevance and usefulness of technology. Furthermore, PU and BIU form an essential linkage between how employees PEOU and their eventual performance at work within pharmaceutical marketing.

RECOMMENDATIONS

Also, human resource managers should regularly liaise with operational and strategic managers to identify key behavioral gaps that should be addressed using training and development among pharmaceutical executives. Thereby triggering the desired behaviors from field executives.

Therefore, management teams must focus on adapting technology more to suit employees' usability rather than solely focusing on achieving organizational objectives. Hence, educational and interactive sessions should be applied to improve their understanding of technology and competency in using technology. In the same vein, PEOU can be enhanced more when employees use more user-friendly devices that do not impede their sense of creativity, discretion, and performance. Simulation exercises and the role-play demonstrations should be included in training sessions. Therefore, factors influencing positive behavioral inclination towards adopting new and existing technology are advocated.

The study's outcomes add significantly to the existing literature on TAM by validating its use or application among pharmaceutical marketing executives in the context of impact on performance. The adapted TAM supports its use to predict user adoption and performance of marketing executives. Furthermore, the study's findings can be extended to the larger scope of sales and marketing organizations where technology use is fast evolving and in cases where technology adoption among employees is still nascent.

Studies validating and comparing the model between regions and countries are suggested. It would enable the extrapolation of findings to a more extensive audience. A longitudinal study design would enable the comparison of instruments over periods. Furthermore, the study focussed on technology applications without a specific focus on a particular tool. Hence, further research is required to assess the impact of specific technologies on the performance among pharmaceutical executives.

CONCLUSIONS

The study revealed that the adapted TAM has adequate psychometric properties with sufficient construct validity as a measurement tool that management teams can use to assess readiness to use technology and evaluate its impact on performance. The structural model provided evidence of user acceptance with significant path coefficients. The tool showed adequate measurement invariance across work roles, company type, and gender. However, only gender differences in significant paths in the model were evident. The study adds to the literature by extending TAM to include Tech-IMP. Managers should focus on enhancing positive user perception and acceptance by engaging in simulated training before introducing new or advanced technology, ensuring adaptability and flexibility of technology use. The study concludes that strategic and human resource managers should provide training and work environments that enable technology acceptance and usage with due consideration for gender differences.

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