Acta Pharm. Sci. Vol 64:(2), 2026
Original article
DOI: 10.23893/1307-2080.APS64016

# Technology acceptance in community pharmacists: Bridging the gap between pharmacists and digital technologies

Merve MEMİŞOĞLU[1*], Ömer BİLEN[2]

1 Istinye University, Faculty of Pharmacy, Department of Pharmacy Management, Istanbul, Türkiye

2 Bursa Technical University, Faculty of Engineering and Natural Sciences, Department of Data Science and Analytics, Bursa, Türkiye

**ABSTRACT**

This study aimed to explore the factors influencing community pharmacists' adoption of digital technologies. A cross-sectional survey was conducted with 879 pharmacists in Istanbul, using an extended Technology Acceptance Model. The key findings revealed that anxiety significantly hindered adoption, negatively affecting both perceived ease of use (peou) (−0.148) and facilitating conditions (fc) (−0.320 total, −0.270 direct). Peou was the strongest positive predictor of behavioral intention (bi), with total and direct effects of 0.241 and 0.142, respectively, highlighting the importance of user-friendly technology design. Fc played a dual role, positively influencing training (0.247) and subjective norms (sn) (0.355), but negatively affecting self-efficacy (se) (−0.193 total, −0.172 direct). Notably, sn negatively affected se (−0.124), suggesting that social pressure may act as a barrier rather than a facilitator. These findings highlight the necessity for comprehensive strategies addressing not only technical usability but also organizational support and social dynamics.

**Keywords:** Technology Acceptance Model (TAM), community pharmacists, digital technology, pharmacy practice

* Corresponding author: Merve MEMİŞOĞLU
E-mail: merve.memisoglu@istinye.edu.tr
ORCIDs:
Merve MEMİŞOĞLU: 0000-0002-8068-6836
Ömer BİLEN: 0000-0001-7198-8421
(Received 25 Sep 2025, Accepted 23 Jan 2026)

© Medipol University Press / ISSN: 2636-8552

## INTRODUCTION

Digital technologies have rapidly transformed healthcare delivery and patient expectations, requiring healthcare professionals to develop and continuously update digital competencies. As highly accessible frontline providers, community pharmacists are increasingly expected to integrate digital technologies into daily practice. This study examines the factors influencing pharmacists' adoption of digital technologies and identifies strategies to support effective implementation.

Evidence suggests that technology integration in pharmacy practice improves productivity, quality of care, financial performance, and job satisfaction[1]. Robotic systems optimize medication distribution, particularly in hospital pharmacies[2], while mobile technologies support patient monitoring, medication adherence, and clinical decision-making[3,4]. Despite these advantages, adoption remains limited; only 13.2% of community pharmacists use mobile health applications, mainly due to low awareness, trust issues, insufficient digital literacy, and limited confidence[5,6].

Beyond mobile tools, technologies such as virtual reality (VR), cloud computing, and health information technology (HIT) are increasingly applied in pharmacy practice. VR has demonstrated potential in training and patient counseling but faces cost and validation barriers[7]. Cloud computing facilitates data exchange yet raises privacy and security concerns[8]. Although pharmacists commonly use computers, access to advanced databases and specialized software remains limited, highlighting the need for training beyond basic digital skills[9]. HIT systems—including drug databases, telemonitoring tools, and personalized digital interventions—have been shown to enhance patient safety and medication adherence[10-13].

In Türkiye, prior TAM-based research focused primarily on the Medula system, limiting generalizability to broader digital technologies[14]. Other studies emphasize the growing importance of mobile technologies, electronic health records, data security, and technology-supported research in pharmacy practice[15]. However, contemporary pharmacy practice increasingly involves a wide range of digital innovations, including the Internet of Things, artificial intelligence, blockchain, wearable technologies, and cybersecurity.

Accordingly, this study investigates the determinants of digital technology adoption among participating community pharmacists in Istanbul by examining interactions between individual, technological, and implementation-related factors. By extending the TAM to incorporate these dimensions, the study provides region-specific evidence and proposes practical strategies to support digital transformation in community pharmacy practice.

## METHODOLOGY

### Research model

To understand the factors influencing the adoption of digital technologies by community pharmacists, a research model was developed. This study builds upon the original TAM, which includes perceived usefulness (pu) and perceived ease of use (peou) and expands it to incorporate key external variables: anxiety (anx), training, and subjective norms (sn).

The model structure and hypothesized relationships were developed following an extensive literature review based on TAM and UTAUT frameworks. To ensure contextual relevance and clarity of the questionnaire items, experienced community pharmacists (n=5), each with over 10 years of professional experience and prior exposure to digital technologies in pharmacy practice, were consulted solely to assess face validity, clarity, and practical applicability. A pre-test of the questionnaire was then conducted with 20 community pharmacists, after which minor adjustments were made, resulting in the final version of the questionnaire. These adjustments were limited to item wording and did not result in any modification of the theoretical model or hypothesized relationships.

Following ethical approval, a cross-sectional survey was conducted through face-to-face interviews with 879 pharmacists in Istanbul, yielding a 95% confidence interval with a ± 3.00% margin of error. Istanbul was selected as the study setting due to its representation of approximately one-fifth of all pharmacies in Türkiye. The study population was stratified according to Istanbul's 40 administrative districts, and pharmacies within each district were randomly selected to ensure proportional representation based on the number of pharmacies per district. As proportional allocation was applied, no post-stratification weighting was required. Data collection took place between April and June 2019.

The survey consisted of 25 items divided into two sections. Section A included socio-demographic and professional characteristics (6 items) and was analyzed using descriptive statistics. Section B comprised 19 items assessing behaviors and attitudes toward digital technologies, measured on a 5-point Likert scale ranging from "Strongly disagree" (1) to "Strongly agree" (5), and analyzed using models based on TAM and UTAUT.

Findings related to advanced technology medicines collected within the same survey instrument have been reported in a separate publication[16]. Except for socio-demographic variables, the questionnaire items used in the present study did not overlap with those included in the previously published research. Accordingly, this article focuses specifically on pharmacists' attitudes toward digital technologies within the framework of TAM.

### Technology acceptance model

TAM, derived from the Theory of Reasoned Action (TRA)[17] focuses on the cognitive processes involved in individuals' adaptation to new technologies[18-19]. Empirical studies have shown that TAM explains a significant portion of variance in usage intention and behavior, although inconsistently across different user types and systems[19]. Consequently, many studies have sought to extend the TAM model by incorporating external variables[20-21]. Our study is grounded in the model developed by Aggelidis et al. (2009), which is based on the UTAUT model[22-24]. The dependent variable in this study is behavioral intention to use bi, defined as an individual's conscious decision to accept or use a technology. Aggelidis et al. (2009) proposed that technology acceptance should be examined across three distinct contexts: individual, technological, and implementation[22].

The specific definitions of these contexts are as follows:

### Technological context

**Perceived ease of use (peou):** The degree to which a pharmacist believes that using a particular system would be free of effort.

**Perceived usefulness (pu):** The degree to which a pharmacist believes that using *a* specific application system will increase his or her job performance.

### Individual context

**Attitude towards using (atu):** A pharmacist's positive or negative feeling about using an information system.

**Self-efficacy (se):** A pharmacist's perception of his or her capability to successfully perform a particular task or attain a targeted outcome.

**Anxiety (anx):** A pharmacist's apprehension or fear when faced with the possibility of using technology.

### Organizational (implementation) context

**Facilitating conditions (fc):** The degree to which a pharmacist believes that a satisfactory organizational and technical infrastructure exists to support the use of the system.

**Training:** A pharmacist's perception of training programs on information system use before and during its operation.

**Subjective norms (sn):** The perceived social pressure pharmacists feel to perform or not perform certain behaviours.

### Statistical analysis

Statistical analysis of the results was conducted using Student's t-test and Welch's Test. Path analysis was employed to examine the extent and nature of relationships defined in the literature based on data obtained from the survey. The data were analyzed using Structural Equation Modeling (SEM) to test the most appropriate model grounded in theoretical relationships. Path analysis, a technique within SEM, shares structural similarities with classical regression analysis and allows for the examination of theoretically grounded relationships among multiple variables simultaneously. Rather than testing all possible variable combinations, this approach focuses on identifying the most appropriate model based on established theoretical frameworks.

Since the constructs were modeled as single-indicator latent variables derived from composite scores, traditional item-level reliability measures such as Cronbach's alpha, Composite Reliability (CR), and Average Variance Extracted (AVE) were not applicable. This modeling strategy is consistent with prior TAM- and UTAUT-based studies that emphasize theory-driven structural relationships and model parsimony.

Accordingly, construct validity was assessed at the model level using confirmatory factor analysis (CFA) and global goodness-of-fit indices. The model demonstrated excellent fit (CFI = 1.000, IFI = 1.000, RMSEA = 0.000), providing strong evidence for the adequacy of the measurement approach and the validity of the latent constructs**.** In addition, the correlation matrix among latent variables is provided to support discriminant validity.

## RESULTS and DISCUSSION

The distribution of socio-demographic characteristics amongst the participating community pharmacists is presented in Table 1.

**Table 1.** Socio-demographic characteristics of community pharmacists

| Socio-demographic Variables | Frequency (n=879) | Percent % |
|---|---|---|
| **Age** | | |
| <26 | 44 | 5,0 |
| 26-30 | 169 | 19,2 |
| 31-40 | 295 | 33,6 |
| 41-50 | 215 | 24,5 |
| 51-60 | 86 | 9,8 |
| >60 | 70 | 8,0 |
| **Gender** | | |
| Male | 408 | 46,4 |
| Female | 471 | 53,6 |
| **Education level** | | |
| Bachelor's degree | 755 | 86,1 |
| Master's degree | 104 | 11,8 |
| Doctorate | 18 | 2,1 |
| **Years of practice** | | |
| 1-5 years | 192 | 21,8 |
| 6-10 years | 205 | 23,3 |
| 11-15 years | 169 | 19,2 |
| 16-20 years | 86 | 9,8 |
| More than 21 years | 227 | 25,8 |
| **Location of community pharmacy** | | |
| Neighborhood pharmacy | 121 | 13,8 |
| Pharmacy on a street | 415 | 47,2 |
| Pharmacy near a hospital | 218 | 24,8 |
| Pharmacy near a family health center | 120 | 13,7 |
| Pharmacy in a mall | 5 | 0,6 |

Before testing the structural model, the correlations among all variables were examined to assess the magnitude and direction of bivariate relationships, to ensure the absence of multicollinearity, and to verify consistency with theoretical expectations. All correlation coefficients were below commonly accepted thresholds for multicollinearity, indicating that the variables were sufficiently distinct for inclusion in the SEM analysis. Table 2 presents the correlation matrix of the variables included in the model.

**Table 2.** Correlation matrix

| Variable | anx | peou | pu | fc | sn | training | se | atu | bi |
|---|---|---|---|---|---|---|---|---|---|
| anx | 1.000 | -0.148 | -0.056 | -0.320 | 0.004 | -0.090 | 0.022 | -0.052 | -0.052 |
| peou | -0.148 | 1.000 | 0.379 | 0.333 | 0.118 | 0.159 | 0.105 | 0.138 | 0.241 |
| pu | -0.056 | 0.379 | 1.000 | 0.289 | 0.103 | 0.273 | 0.120 | 0.114 | 0.204 |
| fc | -0.320 | 0.333 | 0.289 | 1.000 | 0.355 | 0.247 | -0.193 | 0.111 | 0.059 |
| sn | 0.004 | 0.118 | 0.103 | 0.355 | 1.000 | 0.000 | -0.124 | -0.012 | -0.001 |
| training | -0.090 | 0.159 | 0.273 | 0.247 | 0.000 | 1.000 | 0.094 | 0.069 | 0.192 |
| se | 0.022 | 0.105 | 0.120 | -0.193 | -0.124 | 0.094 | 1.000 | 0.094 | 0.011 |
| atu | -0.052 | 0.138 | 0.114 | 0.111 | -0.012 | 0.069 | 0.094 | 1.000 | 0.122 |
| bi | -0.052 | 0.241 | 0.204 | 0.059 | -0.001 | 0.192 | 0.011 | 0.122 | 1.000 |

## Model fit analysis

The chi-square value for the model is 12.969, with 13 degrees of freedom. The ratio of the chi-square value to the degrees of freedom is 0.997, which is less than 2.0, indicating a good model fit.

The goodness-of-fit criteria obtained from the model are as follows: IFI = 1.000, CFI = 1.000, and RMSEA = 0.000, all of which indicate an excellent model fit.

## Variance explained for dependent variables in the model

The endogenous variables in the model are explained at the following rates: fc 39.7%, pu 15.5%, atu 15.1%, training 14.3%, and bi 13.9%. The explanation rates for other variables are: sn 8.4%, se 4.5%, and peou 2.8%.

**Table 3.** Squared multiple correlations

| Variable | Estimate |
|---|---|
| anx | 0.000 |
| peou | 0.028 |
| pu | 0.155 |
| fc | 0.397 |
| sn | 0.084 |
| training | 0.143 |
| se | 0.045 |
| atu | 0.151 |
| bi | 0.139 |

Table 3 presents the explained variance ($R^2$) for each dependent variable in the model. The variable for fc accounts for the highest explained variance at 39.7%, followed by pu at 15.5%, atu at 15.1%, training at 14.3%, and bi at 13.9%.

**Measured direct effects in the model**

As shown in Table 4, the direct effects reveal several meaningful relationships among the variables in the model.

**Table 4.** Direct effects in the model (regression weights)

| | | | Estimate | S.E. | C.R. | P |
|---|---|---|---|---|---|---|
| peou | <--- | anx | -0.148 | 0.029 | -5.062 | *** |
| pu | <--- | peou | 0.379 | 0.030 | 12.639 | *** |
| fc | <--- | peou | 0.224 | 0.025 | 8.823 | *** |
| fc | <--- | pu | 0.289 | 0.026 | 11.078 | *** |
| fc | <--- | anx | -0.270 | 0.021 | -13.144 | *** |
| training | <--- | pu | 0.202 | 0.033 | 6.034 | *** |
| training | <--- | fc | 0.247 | 0.037 | 6.731 | *** |
| sn | <--- | fc | 0.355 | 0.040 | 8.944 | *** |
| sn | <--- | anx | 0.117 | 0.031 | 3.823 | *** |
| se | <--- | peou | 0.103 | 0.044 | 2.332 | 0.020 |
| se | <--- | pu | 0.157 | 0.047 | 3.342 | *** |
| se | <--- | fc | -0.172 | 0.054 | -3.194 | 0.001 |
| se | <--- | training | 0.094 | 0.045 | 2.095 | 0.036 |
| se | <--- | sn | -0.124 | 0.041 | -3.047 | 0.002 |
| atu | <--- | pu | 0.053 | 0.023 | 2.361 | 0.018 |
| atu | <--- | peou | 0.061 | 0.021 | 2.849 | 0.004 |
| atu | <--- | training | 0.060 | 0.022 | 2.793 | 0.005 |
| atu | <--- | fc | 0.114 | 0.026 | 4.473 | *** |
| atu | <--- | se | 0.094 | 0.016 | 5.774 | *** |
| bi | <--- | pu | 0.140 | 0.035 | 3.955 | *** |
| bi | <--- | peou | 0.142 | 0.033 | 4.297 | *** |
| bi | <--- | training | 0.184 | 0.035 | 5.319 | *** |
| bi | <--- | atu | 0.122 | 0.053 | 2.281 | 0.023 |

- Peou decreases as anx increases (-0.148).
- Pu increases with higher peou (0.379).
- Fc are positively influenced by both pu (0.289) and peou (0.224), but are negatively impacted by anx (-0.270). The most significant influence on fc is from pu.
- Training increases as fc (0.247) and pu (0.202) increase, with fc being the most significant factor affecting training.

- Sn increases with both fc (0.355) and anx (0.117), where fc has the strongest effect on sn.
- Se is positively influenced by pu (0.157), peou (0.103), and training (0.094). In contrast, it is negatively affected by fc (-0.172) and sn (-0.124), with fc being the most influential variable.
- All variables affecting atu have a positive impact, listed in descending order as fc (0.114), se (0.094), peou (0.061), training (0.060), and pu (0.053).
- All variables that directly influence bi show a positive effect, with training (0.184), peou (0.142), pu (0.140), and atu (0.122) being the significant contributors.

## Measured indirect effects in the model

As presented in Table 5, the indirect effects in the model are generally modest in magnitude, indicating that most relationships operate primarily through direct paths rather than through multiple mediating variables.

**Table 5.** Measured indirect effects in the model

| | anx | peou | pu | fc | sn | training | se | atu |
|---|---|---|---|---|---|---|---|---|
| peou | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| pu | -0.056 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| fc | -0.049 | 0.109 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| sn | -0.113 | 0.118 | 0.103 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| training | -0.090 | 0.159 | 0.071 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| se | 0.022 | 0.002 | -0.037 | -0.021 | 0.000 | 0.000 | 0.000 | 0.000 |
| atu | -0.052 | 0.078 | 0.061 | -0.003 | -0.012 | 0.009 | 0.000 | 0.000 |
| bi | -0.052 | 0.099 | 0.064 | 0.059 | -0.001 | 0.008 | 0.011 | 0.000 |

- Peou shows no indirect effects.
- Pu is indirectly influenced by anxiety (-0.056), resulting in a negative effect.
- Fc is indirectly influenced by peou (0.109), which has a positive effect, and by anxiety (-0.049), which has a negative effect.
- Sn is indirectly influenced by peou (0.118), pu (0.103), and anxiety (-0.113). Among these, anxiety has a negative indirect effect.
- Training is indirectly influenced by peou (0.159), pu (0.071), and anx (-0.090). Anx again has a negative indirect effect.
- Se is indirectly influenced by peou (0.002), anxiety (0.022), fc (-0.021), and

pu (-0.037). The effects of anxiety and peou are positive.

- Atu is indirectly influenced by pu (0.061), anxiety (-0.052), peou (0.078), sn (-0.012), training (0.009), and fc (-0.003). Here, pu, peou, and training have positive effects.
- Bi is influenced by pu (0.064), fc (0.059), anxiety (-0.052), peou (0.099), se (0.011), training (0.008), and sn (-0.001). Among these, anxiety and sn have negative indirect effects.

### Measured total effects in the model

Table 6 shows that the total effects are largely shaped by direct effects, with only limited contributions from indirect pathways, reinforcing the dominance of direct relationships within the model.

**Table 6.** Measured total effects in the model

| | anx | peou | pu | fc | sn | training | se | atu |
|---|---|---|---|---|---|---|---|---|
| peou | -0.148 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| pu | -0.056 | 0.379 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| fc | -0.320 | 0.333 | 0.289 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| sn | 0.004 | 0.118 | 0.103 | 0.355 | 0.000 | 0.000 | 0.000 | 0.000 |
| training | -0.090 | 0.159 | 0.273 | 0.247 | 0.000 | 0.000 | 0.000 | 0.000 |
| se | 0.022 | 0.105 | 0.120 | -0.193 | -0.124 | 0.094 | 0.000 | 0.000 |
| atu | -0.052 | 0.138 | 0.114 | 0.111 | -0.012 | 0.069 | 0.094 | 0.000 |
| bi | -0.052 | 0.241 | 0.204 | 0.059 | -0.001 | 0.192 | 0.011 | 0.122 |

- In terms of overall effects, peou is not influenced by other variables in the model; its only total effect is the negative influence of anxiety (–0.148).
- Pu is positively influenced by peou (0.379) and negatively affected by anxiety (-0.056), with peou being the most significant variable for pu.
- Fc is positively influenced by both pu (0.289) and peou (0.333), while being negatively affected by anxiety (-0.320). The most influential variable for fc is peou.
- All variables influencing sn have a positive effect. The contributors to sn are fc (0.355), pu (0.103), peou (0.118), and anxiety (0.004), with fc being the most influential.
- Training is positively influenced by pu (0.273), fc (0.247), and peou (0.159), but is negatively affected by anxiety (-0.090). Pu is the most significant variable for training.

- Se is positively influenced by pu (0.120), training (0.094), peou (0.105), and anxiety (0.022), while being negatively affected by fc (-0.193) and sn (-0.124). The most influential variable for se is fc.
- Atu is positively influenced by peou (0.138), pu (0.114), fc (0.111), se (0.094), and training (0.069), but negatively affected by anxiety (-0.052) and sn (-0.012). Peou is the most influential variable for atu.
- Bi is positively influenced by pu (0.204), training (0.192), peou (0.241), atu (0.122), fc (0.059), and se (0.011), while being negatively affected by anxiety (-0.052) and sn (-0.001). The most significant variable for bi is peou.

Figure 1 presents a structural equation model (SEM) that illustrates the relationships among various factors influencing bi in a technological context. This proposed model examines technological, organizational (implementation), and individual factors that affect pharmacists' intentions to adopt technological innovations.

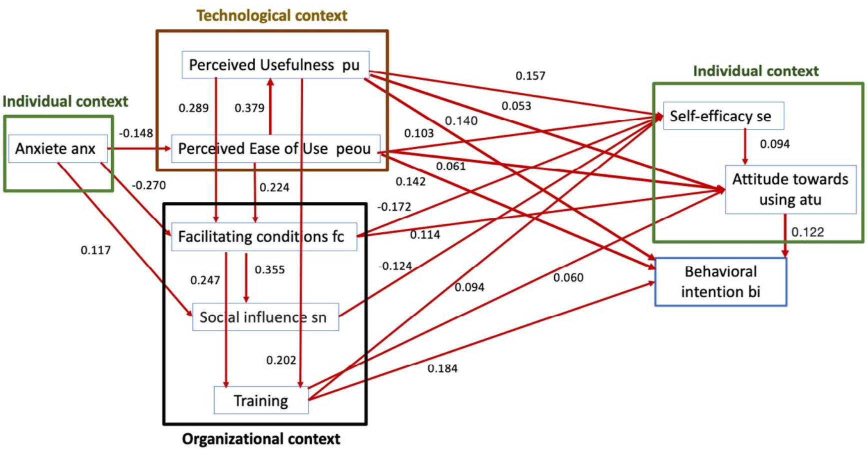


**Figure 1.** Proposed model of technology acceptance: a structural model of direct relationships

The results indicate that pu and peou significantly and positively predict both attitudes and behavioral intentions. Notably, anxiety has a strong negative influence on perceived ease of use. Facilitating conditions are positively impacted by social influence and training. The model underscores perceived ease of use as a crucial predictor of behavioral intention, emphasizing the importance of user-friendly technology design in pharmacy practice.

When considering the combined impact of direct, indirect, and total effects, several key findings emerge, which are listed and detailed below:

**Anx has a pervasive negative effect:** It directly reduces peou (-0.148) and fc (-0.270). Indirectly, it decreases pu (-0.056), fc (-0.049, with a total of -0.320), training (-0.090), and negatively affects both atu and bi (-0.052 each). It also negatively influences sn (-0.113, total of 0.004), indicating that anx is a significant barrier to achieving desired outcomes.

**Peou is a strong positive driver:** Directly increasing pu (0.379), fc (0.224, total of 0.333), se (0.103, total of 0.105), atu (0.061, total of 0.138), and bi (0.142, total of 0.241). Indirect effects further enhance these positive relationships. Peou stands out as the most influential variable affecting fc and bi.

**Pu has a significant effect on other variables:** It directly increases fc (0.289), training (0.202, total of 0.273), se (0.157, total of 0.120), atu (0.053, total of 0.114), and bi (0.140, total of 0.204). Pu is the most influential factor on training.

**Fc has a complex role:** It directly and totally increases training (0.247) and sn (0.355), while also reducing se (-0.172, total of -0.193). Fc is the most influential variable on sn.

**Training and se positively influence atu and bi:** Training has a direct effect on se (0.094), atu (0.060), and bi (0.184). Se directly affects atu (0.094) and has an indirect effect on bi (0.011).

**Sn have a negative effect on Se and a small negative effect on atu and bi:** Direct and total effects on se are (-0.124), while indirect and total effects on atu and bi are (-0.012) and (-0.001), respectively.

Overall, this study reveals several significant findings that illuminate the dynamics of technology adoption among pharmacists:

**Suppressor role of anx:** Anx emerged as a significant suppressor across almost all variables, highlighting the urgent need for strategies to mitigate anxiety levels to promote technology adoption.

**Importance of peou:** Peou was identified as the most influential factor, underscoring the critical need for usability-focused design in technology integration.

**Negative impact of sn:** Contrary to expectations, sn had a negative effect on se, indicating that social pressure may not positively drive technology adoption.

Understanding the determinants of digital technology adoption among community pharmacists is vital for enhancing healthcare delivery. Previous studies in the healthcare sector have consistently identified perceived usefulness as a dominant determinant influencing both attitudes and behavioral intentions directly and indirectly[23-24]. However, these studies often report a lack of significant association with peou, revealing a potential gap in understanding user-centered technology adoption. While our study confirms the significant impact of pu, it diverges by demonstrating that perceived ease of use emerged as the most influential factor in our specific context, emphasizing the need for user-centered design in digital health interventions.

Research involving pharmacists in New Zealand indicates that early adopters of technology are more willing to learn new digital skills and strategize their careers, although fears of job loss hinder their willingness to develop skills[25]. Similarly, studies in Jordan and Brazil highlight barriers to health information technology adoption, including resistance to change, lack of competence, and inadequate training[26,27]. A study in Australia stresses the importance of healthcare authorities supporting community pharmacists as their roles expand, particularly in adapting to advanced technologies. It also emphasizes the need for educating both pharmacists and patients about these technologies, as educational programs can alleviate concerns and address technological knowledge gaps[28].

Building on these findings, our study explored the impact of training and anxiety on digital technology adoption. While training positively contributes to adoption, we observed a pronounced negative effect of anxiety, contrasting with some previous work. This highlights the necessity of addressing anxiety-related barriers for successful technology integration in pharmacy practice. Therefore, implementing anxiety-reduction training programs tailored to pharmacists' specific challenges in adopting new technologies could be highly beneficial. Additionally, establishing technology support groups or forums for pharmacists to share experiences, ask questions, and receive peer support could further reduce anxiety and foster more positive attitudes toward technology integration. Clear communication about the benefits of technology and available support resources may also help alleviate anxiety.

Our study found that fc significantly impacts technology adoption. Although community pharmacies lack the institutional affiliation of hospitals, pharmacy associations and universities should support infrastructure development and information sharing to enhance technology adaptation and research-oriented practices.

Sezgin et al.[14] (2016) examined the TAM using Medula, a Ministry of Health platform integrating electronic health records, and found peou and pu to be important predictors, aligning with our findings. Similarly, Alaşehir et al.[29] (2013) found that peou significantly influenced female pharmacists' behavioral intentions toward Medula, which is consistent with our results. However, our study explored a broader range of technologies, including IoT, AI, and wearable technology, providing a more comprehensive understanding of technology adoption in pharmacies.

Moreover, Aggelidis et al.[22] (2009) highlighted peou as a significant predictor of bi, aligning with our study's emphasis on user-friendly technology design. A crucial distinction, however, is the role of anxiety. While previous studies have shown that anx negatively impacts peou, our study extends this by demonstrating that anxiety acts as a significant suppressor across all variables, thus broadly negatively influencing technology adoption. This reinforces the critical need for anxiety reduction strategies, a finding further emphasized in our research.

As noted in numerous publications, despite the significant impact of technology on optimizing the healthcare system, further investigation into the technology acceptance, needs, and preferences of community pharmacists is necessary. Addressing this gap, our study reveals that peou is a crucial factor in digital technology adoption, while anxiety significantly impedes this process. Therefore, it is vital to focus on developing user-friendly technologies and implementing targeted anxiety-reduction programs to effectively address pharmacists' concerns. For example, technology training, support groups, and mentorship programs may boost pharmacists' confidence in technology, reduce anxiety, and foster a more positive attitude toward adoption.

Looking ahead, future research should prioritize longitudinal studies to validate these findings and explore additional factors, such as organizational and social influences, that may affect technology adoption among community pharmacists. Moreover, healthcare authorities should actively promote initiatives to bridge the digital gap and enhance the overall quality of pharmacy practice.

## Limitations and future research

This study has several limitations that must be acknowledged. First, the cross-sectional design restricts our ability to establish causal relationships between variables. Future research should adopt longitudinal designs, such as panel or cohort studies, to investigate the evolving nature of technology adoption and its long-term effects. Given the rapid pace of technological advancements, replicating this study over time is essential to accurately reflect changing trends and maintain the relevance of the findings.

Second, the sample consisted of pharmacists from a specific region, which may limit the generalizability of the results. Future studies should aim for a more diverse sample of pharmacists from various regions and healthcare settings, including public and private hospitals and community pharmacies, to enhance external validity. Additionally, future research could examine the influence of individual differences, such as personality traits (e.g., openness to experience, adaptability) and prior technology experience (e.g., familiarity with electronic health records, mobile health applications), and on technology adoption among pharmacists.

Third, the constructs in this study were modeled using composite-based single-indicator latent variables, which did not allow for the calculation of traditional item-level reliability indices such as Cronbach's alpha, Composite Reliability, or Average Variance Extracted. Although this modeling approach is theoretically justified and commonly applied in TAM- and UTAUT-based SEM research, future studies could employ multi-item latent constructs to enable more detailed assessment of measurement reliability and convergent validity.

## STATEMENT OF ETHICS

This study adheres to the principles of the Declaration of Helsinki. Ethical approval was granted by the Biruni University Ethical Committee (CSS ref: 2019-27-43). Ethics Sub-Board (Approval No. 143, Date: 25.06.2018).

## CONFLICT OF INTEREST STATEMENT

The authors have no conflicts of interest to declare.

## AUTHOR CONTRIBUTIONS

Design, MM, acquisition of data, MM; analysis of data, ÖB; drafting of the manuscript, MM; critical revision of the manuscript, MM and ÖB; statistical analysis, ÖB; technical or financial support, MM and ÖB; other, MM and ÖB.

## FUNDING SOURCES

This study was supported by the Research Fund of Biruni University. Project No. BAP-2019-01-02.

## ACKNOWLEDGMENTS

Not applicable.

## REFERENCES

1. Kreling DH, Doucette WR, Mott DA, Gaither CA, Pedersen CA, Schommer JC. Community pharmacists' work environments: evidence from the 2004 National Pharmacist Workforce Study. JAPhA, 2006;46(3):331–339. Doi: 10.1331/154434506777069651

2. Barrett M, Oborn E, Orlikowski WJ, Yates J. Reconfiguring boundary relations: robotic innovations in pharmacy work. Organ Sci, 2012;23(5):1448–1466. Doi: 10.1287/orsc.1100.0639

3. Almarsdottir AB, Babar ZUD. Future methods in pharmacy practice research. Int J Clin Pharm, 2016;38(3):724–730. Doi: 10.1007/s11096-016-0300-y

4. Aungst TD. Medical applications for pharmacists using mobile devices. Ann Pharmacother, 2013;47(7-8):1088–1095. Doi: 10.1345/aph.1S035

5. Crilly P, Hassanali W, Khanna G, Matharu K, Patel D, Patel D, et al. Community pharmacist perceptions of their role and the use of social media and mobile health applications as tools in public health. RSAP, 2019;15(1):23–30. Doi: 10.1016/j.sapharm.2018.02.005

6. MacLure K, Stewart D. A qualitative case study of ehealth and digital literacy experiences of pharmacy staff. RSAP, 2018;14(6):555–563. Doi: 10.1016/j.sapharm.2017.07.001

7. Ventola CL. Virtual reality in pharmacy: opportunities for clinical, research, and educational applications. P T, 2019;44(5):267.

8. Ahuja SP, Mani S, Zambrano J. A survey of the state of cloud computing in healthcare. Netw Commun Technol, 2012;1(2):12–19. Doi: 10.5539/nct.v1n2p12

9. Thomas P, Rutter PM. A computer literacy skills profile of pharmacists residing in two counties of England. HILJ, 2008;25(4):288–294. Doi: 10.1111/j.1471-1842.2008.00767.x

10. Kaushal R, Barker KN, Bates DW. How can information technology improve patient safety and reduce medication errors in children's health care? Arch Pediatr Adolesc Med, 2001;155(9):1002–1007. Doi: 10.1001/archpedi.155.9.1002

11. Fuji KT, Galt KA. Pharmacists and health information technology: emerging issues in patient safety. HEC Forum, 2008;20(3):259–275. Doi: 10.1007/s10730-008-9075-4

12. Granger BB, Bosworth HB. Medication adherence: emerging use of technology. Curr Opin Cardiol, 2011;26(4):279–287. Doi: 10.1097/HCO.0b013e328347c150

13. Kaushal R, Bates DW. Information technology and medication safety: What is the benefit? BMJ Qual Saf, 2002;11(3):261–265. Doi: 10.1136/qhc.11.3.261

14. Sezgin E, Özkan Yıldırım S. A cross-sectional investigation of acceptance of health information technology: a nationwide survey of community pharmacists in Turkey. RSAP, 2016;12(6):949–965. Doi: 10.1016/j.sapharm.2015.12.006

15. Babar ZU-D, Scahill S, Nagaria RA, Curley LE. The future of pharmacy practice research — perspectives of academics and practitioners from Australia, NZ, United Kingdom, Canada and USA. RSAP, 2018;14(12):1163–1171. Doi: 10.1016/j.sapharm.2018.01.004

16. Memisoglu M, Bilen Ö. A framework for advanced technology medicines from the perspective of community pharmacists; with or without technology. Braz J Pharm Sci, 2022;58:e20654. Doi: 10.1590/s2175-97902022e20654

17. Fishbein M, Ajzen I. Belief, attitude, intention and behaviour: an introduction to theory and research. Boston: Addison-Wesley; 1975.

18. Davis FD. Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Q, 1989;13(3):319–340. Doi: 10.2307/249008

19. Hu L-T, Bentler PM. Cutoff criteria for fit indexes in co-variance structure analysis: conventional criteria versus new alternatives. Struct Equ Modeling, 1999;6(1):1–55. Doi: 10.1080/10705519909540118

20. Venkatesh V, Davis FD. A theoretical extension of the technology acceptance model: four longitudinal field studies. Manag Sci, 2000;46(2):186–204. Doi: 10.1287/mnsc.46.2.186.11926

21. Venkatesh V, Morris MG, Davis GB, Davis FD. User acceptance of information technology: toward a unified view. MIS Q, 2003;27(3):425–478. Doi: 10.2307/30036540

22. Aggelidis VP, Chatzoglou PD. Using a modified technology acceptance model in hospitals. Int J Med Inform, 2009;78(2):115–126. Doi: 10.1016/j.ijmedinf.2008.06.006

23. Chau PYK, Hu PJ-H. Investigating healthcare professionals' decisions to accept telemedicine technology: an empirical test of competing theories. Inform Manag, 2002;39(4):297–311. Doi: 10.1016/S0378-7206(01)00098-2

24. Hu PJ, Chau PYK, Sheng ORL, Tam KY. Examining the technology acceptance model using physician acceptance of telemedicine technology. JMIS, 1999;16(2):91–112. Doi: 10.1080/07421222.1999.11518247

25. Martini N, Sajtos L, Idio L, Kaur M, Sweeney N, Zhang C, et al. The future of pharmacy work: How pharmacists are adapting to and preparing for technology infusion. ERCSP, 2024;15:100472. Doi: 10.1016/j.rcsop.2024.100472

26. Rawashdeh M, Alzoubi KH, Muflih S, Al-Azzam S, Halboup AM. Community pharmacists' attitudes, prior experience, and perceived barriers to informatics: a cross-sectional study from a developing country. IMU, 2024;46:101473. Doi: 10.1016/j.imu.2024.101473

27. Néri EDR, Meira AS, da Silva Vasconcelos HB, Woods DJ, de França Fonteles MM. Knowledge, skills and attitudes of hospital pharmacists in the use of information technology and electronic tools to support clinical practice: a Brazilian survey. PloS One, 2017;12(12):e0189918. Doi: 10.1371/journal.pone.0189918

28. Ogundipe A, Sim TF, Emmerton L. What is the landscape of community pharmacy technology? Critiquing contemporary digital innovation in the Australian context. Pharm Pract, 2024;22(4):1–16:3038. Doi: 10.18549/pharmpract.2024.4.3038

29. Alaşehir O, Sezgin E, Özkan S. The role of gender in pharmacists' attitudes towards e-pharmacy application. Procedia Soc Behav Sci, 2013;83:1111–1115. Doi: 10.1016/j.sbspro.2013.06.208