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# Exploring technology adoption measures among academicians and its influence on their research practices and performance

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**Abstract**

The advent of technology may dramatically alter academic research and performance. This study uses the Unified Theory of Adoption and Use of Technology (UTAUT) and Task-Technology Fit (TTF) theories to examine how technology adoption influence Research Performance conducted with sample size of 1,354 South Indian private institution Assistant Professors, with perception as a moderating factor. The research uses Structural Equation Modelling (SEM) with SmartPLS 4.0 to reveal that Performance Expectancy (PE) greatly influence Behavioral Intention (BI) to adopt technology. Higher Performance Expectancy (PE) leads to a stronger intention to use technology. Effort Expectancy (EE) also boosts BI, emphasizing the role of usability in setting user intentions. Technology adoption depends on Social Influence (SI), along with peer and social norms affect BI. Effective technology adoption requires Facilitating Conditions (FC) and enough resources and infrastructure. Task Characteristics (TC) and Technology Characteristics (TCh) greatly alter Task-Technology Fit (TTF), which enhances research procedures. TTF improves research practices but hurts research performance, demonstrating that improved techniques do not necessarily translate to better performance ratings, highlighting the intricacy of task-technology compatibility and research results.

**KEYWORDS:** Academicians, Research Practices, Research Performance, UTAUT, TTF.

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## 1. Introduction

Technology has revolutionized academic research, helping researchers improve efficiency and depth (Vega et al., 2016). Research was formerly constrained by manual techniques and physical resources. Digital resources, e-contents, and improved technology have expedited research methods to satisfy digital era expectations (Oguguo et al., 2023; Sabino & Almenara, 2021). Today's academic landscape relies on technology for data collection, processing, and dissemination, which improves research performance when Task-Technology Fit (TTF) is achieved by aligning Task Characteristics (TC) with Technological Characteristics (TCh).

Adoption of academic technology is influenced by Performance Expectancy (PE), Effort Expectancy (EE), Behavioral Intention (BI), and Social Influence (SI). PE and EE assess expected research success and

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technological ease, whereas BI measures social influences on technology adoption (Zhang et al., 2020). Technology integration requires infrastructure and assistance (Omotayo & Haliru, 2019).

Perception (PER) moderates Use Behavior (UB), TTF, Research Practices (RP), and Research Performance (RPf), impacting research technology adoption (Ahmed et al., 2018). Positive impressions improve research habits and performance, promoting creativity and academic achievement (Hoppmann et al., 2020; Alonso, 2009). Using technology strategically and understanding its aspects might increase research productivity and innovation (Padilla-Hernández et al., 2019; Agustí López et al., 2023; Ozer Sanal, 2023).

## 2. Theoretical Framework

Today's fast-paced technological world requires understanding how academics use technology to improve research. The Unified Theory of Acceptance and Use of Technology (UTAUT) and Task-Technology Fit (TTF) provide light on technology uptake and efficacy in academic research. UTAUT, created by (Venkatesh et al., 2016), uses 8 technology acceptance models to describe user intents and behaviors, highlighting four essential factors: PE, EE, SI, and FC. PE refers to technology-enhanced research output, whereas EE refers to ease of use. SI measures the effect of important people on technology adoption, while FC supports research procedures organizationally and technologically. (Ayaz & Yanartas, 2020) demonstrate UTAUT's relevance to academic technology uptake.

The TTF, established by (Goodhue & Thompson, 1995), suggests that technology's efficacy relies on its fit with research activities. TTF is crucial in academic research, because technology's productivity depends on its compatibility with research activities, according to (Aljarboa & Miah, 2020) show that UTAUT and TTF are useful for research technology adoption analysis. Hence, TTF acts as prerequisite for expected research outcomes. This comprehensive approach provides a solid foundation for assessing academic technology usage and improving research performance (Alwadain et al., 2024).

## 3. Conceptual Framework and Hypothesis Development

### 3.1 Performance Expectancy (PE) and Behavioral Intention (BI)

PE shapes BI to utilize technology, especially in research and academic contexts. PE implies that a certain system improves performance, as it ease the flow of research process and execution (Faida et al., 2022). Technology's claimed benefits to efficiency, education, and research encourage its adoption in academia. Researchers who believe technology improves performance are more inclined to use it (Utomo et al., 2021). PE not only strongly impacts higher education use of online learning and research technology. Chao 2019, demonstrated that PE is significant in predicting BI towards e-records, documents required for drafting research papers. Academics are more likely to utilise technology if they feel it helps them achieve research objectives, such as accessing digital materials. PE is intimately linked to education technology uptake in the UTAUT paradigm.

*Hypothesis 1*: Performance Expectancy (PE) positively influences Behavioral Intention (BI) among academicians.

### 3.2 Effort Expectancy (EE) and Behavioral Intention (BI)

Unified Theory of Acceptance and Use of Technology (UTAUT) component Effort Expectancy (EE) strongly influence academics' BI to embrace new technology. In technology, EE is perceived ease of use (Ayaz & Yanartaş, 2020). Academics' desire to adopt technology depends on user-friendliness. Academics use technology that is simple to use and operate, according to research. If a learning management and mechanism system is easy, academicians are more likely to use it. EE strongly influence BI in educational and other situations, according to empirical investigations. (Fishman et al., 2020) showed a strong association between academic professionals' use of e-record management systems and its perceived ease of use, emphasizing the need for user-friendly designs to increase technology adoption.

*Hypothesis 2*: Effort Expectancy (EE) positively influences Behavioral Intention (BI).

### 3.3 Social Influence (SI) and Behavioral Intention (BI)

SI is how others' thoughts, actions, and behaviours affect an individual's ideas and choices, especially academics' technology uptake, specially the peer to peer. BI shows motivation to do a behavior. The influence of SI on BI is considerable, since academics may regard technology as desirable or required when backed by reputable leaders and support in their field. Technology adoption becomes desirable and anticipated in their professional community due to normative pressure. To remain relevant and competitive increases this ambition (Aditia et al., 2018). Peer praise boosts BI and encourages technological adoption. SI starts and amplifies BI, promoting academic technology adoption (Izuma, 2017).

*Hypothesis 3*: Social Influence (SI) positively affects Behavioral Intention (BI)

3.4 Facilitating Conditions (FC) and Use Behavior (UB)

FC are an individual's belief that organisational and technical assistance exists to employ technology. Academics need this notion, which underpins (Venkatesh et al., 2003) Unified Theory of Acceptance and Use of Technology (UTAUT). It includes training, technical assistance, and infrastructure (e.g., internet connection, devices, and software) for educational technology usage. FC eliminates technology adoption hurdles, boosting academics' confidence in adopting technology for teaching, research, and administration. By reducing barriers to new technology use, (Kamarozaman & Razak, 2021) found that this improves their Use Behaviour (UB). The cognitive strain of learning new systems is reduced by trustworthy technical assistance, enabling consistent technology usage (Hameed, 2024).

*Hypothesis 4*: Facilitating Conditions (FC) positively influence Use Behavior (UB).

3.5 Behavioral Intention (BI) and Use Behavior (UB)

Understanding academic technology involvement requires BI and UB. BI precedes UB and indicates a person's technology adoption readiness. According to (Hameed et al., 2024), BI towards technology learning shows how academics expect to employ technology in their research, based on perceived ease of use, usefulness, and attitude. In contrast, UB is the real-world use of technology, demonstrating involvement. (Brezavšček, 2016) demonstrates how taking use of statistical software in Slovenian social sciences leads to its application in academic work. The Theory of Reasoned Action (TRA) and Technology Acceptance Model (TAM) show that strong BI typically leads to technology usage.

*Hypothesis 5*: Behavioral Intention (BI) positively influences Use Behavior (UB).

3.6 Task Characteristics (TC), Technology Characteristics (TCh), and Task-Technology Fit (TTF)

Task-Technology Fit (TTF) depends on Task Characteristics (TC) and Technology Characteristics (TCh), which greatly affects academic technology use. Academic work characteristics like complexity and data analysis needs determine the technical assistance required to improve performance. Large-scale data processing requires complex analytical techniques. Technology Characteristics (TCh) including usability and adaptability must meet academic demands (Ma & Jing, 2023). This alignment affects productivity and user pleasure, making it essential for high TTF (Shih, 2013). TTF depends on TC and TCh, hence aligning these variables is crucial for optimising technology usage, task performance, and academic efficiency (Hoppmann et al., 2020).

*Hypothesis 6*: Task Characteristics (TC) positively influence Task-Technology Fit (TTF)

*Hypothesis 7*: Technology Characteristics (TCh) positively influence Task-Technology Fit (TTF)

3.7 Task-Technology Fit (TTF) and Research Practices (RP)

Modern culture is moulded by and influenced by technology (Orlikowski, 2000). Digital learning and technology greatly affect research. Digital technologies have a worldwide influence on education, especially academically (Cook & Triola, 2014; Talebian, 2014). This development has boosted education, research, and academia (Oguguo et al., 2023). The Task-technological Fit (TTF) idea betters researcher performance by matching task needs with technological capabilities. It states that task requirements influence technological effectiveness TTF enhances research by aligning technology with tasks, expediting data collecting, promoting communication, and increasing efficiency and quality (Hernández et al., 2015; Cigdem & Oncu, 2024; Doğan & Kalinkara, 2024).

*Hypothesis 8*: Task-Technology Fit (TTF) positively affects Research Practices (RP).

3.8 Task-Technology Fit (TTF) and Research Performance (RPf)

TTF helps academics improve RPf by supporting research activities with technology. Shih (2013) notes that optimum TTF reduces research work, enabling concentration on essential tasks and improving efficiency and production. (Ma, Lixia, & Jing, 2023) note that excellent fit enhances research findings and confirms TTF perception, producing a positive feedback cycle. Better research findings increase trust in technological instruments, improving TTF perception and research technology integration, according to (ALKursheh, 2024). High TTF increases researcher happiness, motivation, and productivity, increasing research outputs and boosting technology adoption (Talebian et al., 2014). Strong TTF promotes innovation and knowledge development, enhancing TTF and RPf's reciprocal advantages. Effective TTF helps academics and their RPf.

*Hypothesis 9*: Task-Technology Fit (TTF) positively influence Research Performance (RPf)

3.9 Use Behavior (UB) and Research Practices (RP)

UB with R, Python, SmartPLS, AMOS, and other AI applications is growing in academia (Gruzd, Staves & Wilk, 2012). Although these technologies are transforming research, many institutions still have incompatible software and communication infrastructures that impede innovation (Unsworth, 2008). Recent studies have substituted technology performance with research impacts (Dwivedi et al., 2019). (Menzies & Newson, 2007) found that new technology enhanced research skills and productivity but lowered creativity. To explain sustained UB), (Hong et al., 2006) utilise TAM model and emphasise that user learning and perceived usefulness drive engagement (Xu et al., 2011). Data collection and analysis are easier with digital technology, improving digital literacy and research efficiency (Agudo-Peregrina et al., 2014)

*Hypothesis 10*: Use Behavior (UB) positively influences Research Practices (RP).

### 3.10 Use Behaviour (UB) and Research Performance (RPf)

RPf depends on UB, especially technology use. RPF evaluates academic work's effect and efficacy, whereas UB uses technology for research and performance. According to (Bazeley, 2010), incorporating technology to RP may enhance productivity and efficiency when UB matches tasks. When tasks and technology match, RPf rises. According to (Aboagye et al., 2021), choosing research-enhancing technologies improves research performance by strategically matching research tasks with accessible technology. (Gruzd, Staves, & Wilk, 2012) demonstrate that digital networking and information sharing boost research efficacy and technology uptake. When task complexity and researcher skill meet, technology use enhances RPf, (Unsworth, 2008). Technological literacy affects RPf and digital literacy encourages technology use and research (MohdRasdi et.al, 2023). Effective technology use boosts research productivity and links UB and RPf.

*Hypothesis 11*: Use Behaviour (UB) positively influence Research Performance (RP)

### 3.11 Research Practices (RP) and Research Performance (RPf)

In today's academic environment, succeeding in RPf measures affirms our reputation as researchers at both personal and institutional levels, gaining time and money for future work and boosting esteem. Traditional RPf measurements include publication production, citation counts, and quality indices (Bazeley, 2010). Technology improves research efficiency and efficacy, increasing RPf. Digital technologies and platforms simplify data administration and publishing, saving time and expanding reach. (Javed et al., 2020) stress the need of investing in technology and training to improve research. Alonso et al. (2009) further note that improved Bibliometric tools monitor citations and analyse work impact, enhancing measures like the h-index and i10 index and creating a dynamic research environment.

*Hypothesis 12*: Research Practices (RP) positively influence Research Performance (RPf).

### 3.12 Moderation by Perception

#### *3.12.1 Perception (PER) as Moderation between Use Behavior (UB) and Research Practices (RP)*

UB is how researchers access, process, and share information using technology, impacted by fast tech breakthroughs and the digitalisation of research resources. Researchers' use of new innovation is heavily influenced by behavioural characteristics like adaptation and openness. Researchers that adapt effectively to technological changes use digital technologies more easily, increasing their RP (Ozer Sanal, 2023). (Atiqah et al., 2024) note that UB—how often, how, and why researchers use technology—affects their RPf in a tech-centric setting. PER moderates UB substantially; favourable evaluations of technology as user-friendly and useful boost engagement and innovation. Conversely, unfavourable opinions may limit technology utilisation and research efficiency (González & Leiva, 2022). PER affects technology acceptance and usage, with value views impacting researchers' relationships and RP continuity.

*Hypothesis 13*: Perception (PER) moderates the relationship between Use Behavior (UB) and Research Practices (RP).

#### *3.12.2 Perception (PER) as Moderation between Task-Technology Fit (TTF) and Research Practices (RP)*

User experience, ease of use, and perceived usefulness influence technology perception (PER), and its moderating impact may increase or decrease these perceptions. Positive moderating effects boost perceived usefulness, contentment, and adoption, whereas negative effects lower perceived advantages and raise resistance (Azam et al., 2023). (Mutahar et al., 2019) found that high technology perceived value improves TTF and user acceptability. This shows that researchers improve technology adoption when its qualities match their work. (Omotayo & Haliru, 2019) add that PER moderates TTF's effect on academic research practices. Data privacy and reliability may slow technology adoption, whereas (Sun & Zhang, 2006) note that PER influences technology-task fit and research practice adoption.

*Hypothesis 14*: Perception (PER) moderates the relationship between Task-Technology Fit (TTF) and Research Practices (RP)

#### *3.12.3 Perception (PER) as Moderation between Research Practices (RP) and Research Performance (RPf)*

PER moderates the relationship between RP and RPf, especially academics' technology utilisation. Academics see technology's influence on research as PER. A positive PER may boost RP and research outputs, whereas a negative perception may restrict technology's benefits. (González & Olivencia, 2022) stress that academics' technical viewpoints considerably affect research integration. Technologies that boost research performance are supported by positive attitudes. Good perceptions of tool usefulness and simplicity of use encourage tool usage, which affects study success in (Ozer, 2023). Perception (PER) stimulates technology use and improves research performance, according to (Ismail et al., 2024). Perception (PER) affects adaptability and resilience, enhancing research outcomes. Perception (PER) is linked to self-efficacy, with confident academics conquering difficult tasks, positive perceptions increase research effectiveness by fostering innovation and teamwork (Hong et al., 2006). These studies suggest that positive technological attitudes benefit research.

*Hypothesis 15*: Perception moderates the relationship between Research Practices (RP) and Research Performance (RPf).

## 4. Methodology

The study utilizes a non-experimental design ex post facto by surveys, as it effectively captures and analyze the present state of technology adoption among academicians, as well as its influence on their research practices and performance. Convenience sampling was employed to select 1,354 academicians from private universities in South India, and data was analysed employing the model mentioned in Figure 1, using SmartPLS 4.0 with Structural Equation Modelling (SEM) to examine the relationships between the constructs. In alignment with ethical standards, all participants were thoroughly briefed on the confidentiality protocols, ensuring that their privacy would remain protected. Moreover, the integrity and accuracy of the information collected were diligently safeguarded to maintain the study's credibility.

The study is grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT) and Task-Technology Fit (TTF) theories, which explain how perceived usefulness, ease of use, and task-technology alignment influence technology adoption.

Reliability and validity of the constructs were ensured using the Fornell-Larcker criterion and Heterotrait-Monotrait (HTMT) ratio, confirming the distinctiveness and accuracy of the constructs. Path analysis in the structural model revealed that technology adoption, when aligned with research tasks, significantly enhances research performance. The findings emphasize the importance of supporting academicians in effectively integrating technology into their research practices to improve outcomes in South India's higher education sector.

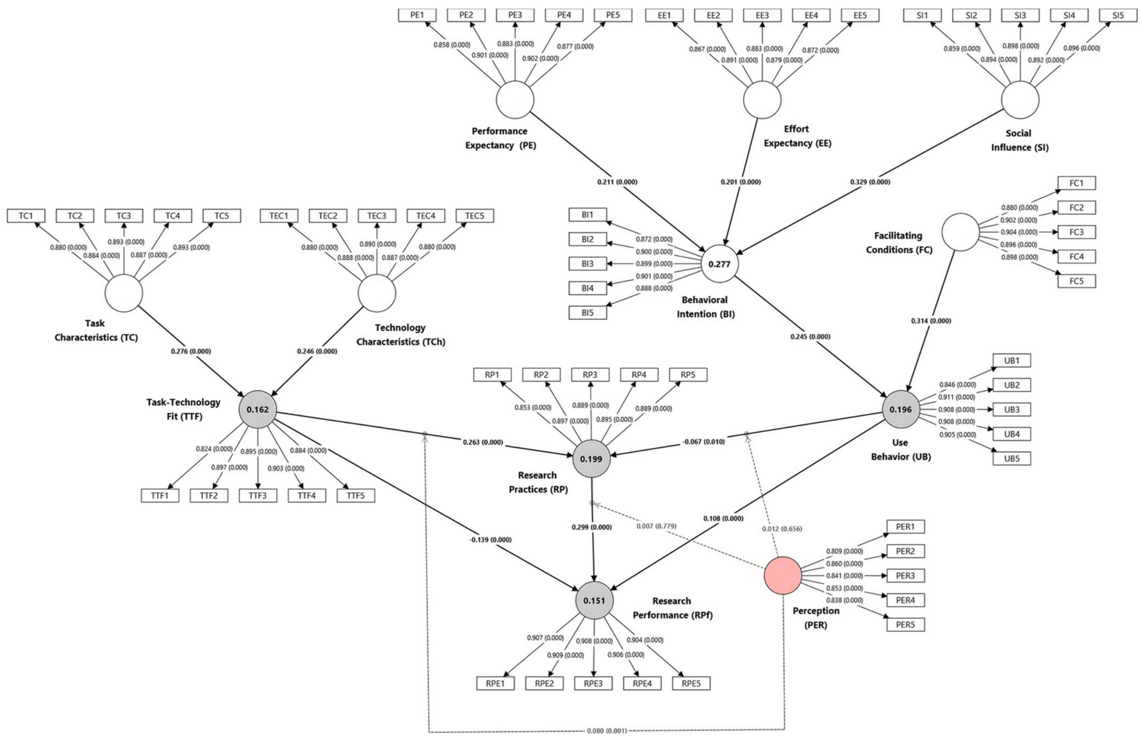


**Figure 1** – Structural Model.

## 5. Data analysis and Findings

To understand technology adoption and its implications on research methods, the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), and Task-Technology Fit (TTF) must be integrated. (Davis 1989) TAM emphasizes individual views like usefulness and ease of use. (Venkatesh et al., 2003) UTAUT includes social impact and conducive situations. TTF, emphasized by (Goodhue & Thompson, 1995), evaluates how effectively technology supports certain activities by aligning technological attributes with task needs. Combining these ideas gives researchers a complete picture of individual, societal, and environmental aspects driving technology adoption. This integrated method illuminates technology's involvement in research performance and reveals obstacles and facilitators at several levels, resulting in more effective interventions and initiatives. The model offers a solid foundation for studying academic technology use's complicated dynamics.

Task Characteristics (TC) and Technology Characteristics (TCh) significantly affect TTF, emphasizing the importance of aligning technology with specific task requirements (Goodhue & Thompson, 1995). TTF further impacts RP, illustrating that well-aligned technology enhances the effectiveness of research activities. The model also shows that both UB and RP directly influence RPf, demonstrating that the quality of RP and the extent of technology use are crucial for achieving better RPf.

Perception (PER) acts as a moderator, altering the relationships between TTF, UB, RP, and RPf, reflecting the importance of individual perceptions in shaping the effectiveness of technology use in research settings. This highlights the nuanced role of perceptions in influencing how well technology adoption translates into improved research performance (Dwivedi et al., 2019). Overall, the model underscores the complex dynamics of technology adoption in academic contexts, illustrating how well-integrated technology and positive perceptions can significantly enhance research productivity and outcomes.

The validity and reliability measures evaluate the model's constructs, assuring high internal consistency, construct validity, and measurement accuracy for dependable conclusions. With a Composite dependability (CR) of 0.947 and a Cronbach's Alpha (α) of 0.932, PE demonstrated high dependability, above the typical criterion of 0.70. The construct's convergent validity is supported by its AVE of 0.782, which is compatible with technology adoption theories that PE predicts BI (Venkatesh et al., 2003). With CR values of 0.944 and 0.949 and AVE values of 0.771 and 0.788, respectively, EE and SI both have excellent psychometric features, consistent with (Venkatesh & Bala's, 2008) extension of the Technology Acceptance Model. A CR of 0.946 and an AVE of 0.777 made TTF dependable for assessing user performance outcomes (Goodhue & Thompson, 1995). With a CR of 0.959 and an AVE of 0.823, RPf was the most reliable, assuring accurate measurement (Hair et al., 2017).

The Fornell-Larcker criterion confirms strong discriminant validity across all constructs, demonstrating that each variable is distinct and accurately reflects its intended concept. The square root of the Average Variance Extracted (AVE) for each construct surpasses its correlations with other constructs, ensuring that each variable shares more variance with its indicators than with any other variable. For instance, BI has an AVE square root of 0.892, exceeding its correlations with other constructs. Similarly, EE, FC, and PE have AVE square roots of 0.878, 0.896, and 0.884, respectively. Other constructs, including SI, TC, TCh, TTF, and UB, also maintain high discriminant validity.

In this model, most HTMT values are below 0.85, proving discriminant validity. BI and EE have moderate correlations, whereas FC and SI have low correlations, confirming their uniqueness. Overall, the HTMT analysis provides good discriminant validity, confirming the model's structural integrity and dependability. Overall, TTF impacts research practices and performance, as it evaluates user task technical assistance. Technology helps scholars analyse data, analyse literature, collaborate, and publish. TTF boosts productivity, accuracy, and data processing with the proper tech. Innovative discoveries, high-quality publications, and academic creativity boost research. TTF links researchers online to increase collaboration and diversity. TTF optimization improves research productivity and repute.

### 5.1 Structural Model Analysis

Referring to the Table 1, the structural model assessment and hypothesis testing results offer valuable insights into the relationships between constructs, underscoring the significance of various predictors on BI, UB, TTF, and RPf. Hypotheses were tested for significance using path coefficients (β), t-values, p-values, and effect sizes ($f^2$), while multicollinearity was assessed through Variance Inflation Factor (VIF) values, all below 5, indicating no multicollinearity issues.

PE significantly influences BI ($\beta = 0.211$, $t = 8.412$, $p < 0.001$), supported by moderate effect size ($f^2 = 0.056$) and aligned with TAM (Davis, 1989). EE also impacts BI ($\beta = 0.201$, $t = 8.744$, $p < 0.001$), as does SI ($\beta = 0.329$, $t = 13.554$, $p < 0.001$) with the largest effect size ($f^2 = 0.135$). FC significantly affect UB ($\beta = 0.314$, $t = 11.817$, $p < 0.001$), and BI influences UB ($\beta = 0.245$, $t = 8.964$, $p < 0.001$).

**Table 1** - Structural model.

| | Hypothesis | VIF | β | SD | t-value | p-value | Supported | f2 |
|---|---|---|---|---|---|---|---|---|
| 1 | Performance Expectancy (PE) -> Behavioral Intention (BI) | 1.104 | 0.211 | 0.025 | 8.412 | 0.000 | Yes | 0.056 |
| 2 | Effort Expectancy (EE) -> Behavioral Intention (BI) | 1.087 | 0.201 | 0.023 | 8.744 | 0.000 | Yes | 0.051 |
| 3 | Social Influence (SI) -> Behavioral Intention (BI) | 1.104 | 0.329 | 0.024 | 13.554 | 0.000 | Yes | 0.135 |
| 4 | Facilitating Conditions (FC) -> Use Behavior (UB) | 1.062 | 0.314 | 0.027 | 11.817 | 0.000 | Yes | 0.116 |
| 5 | Behavioral Intention (BI) -> Use Behavior (UB) | 1.062 | 0.245 | 0.027 | 8.964 | 0.000 | Yes | 0.070 |
| 6 | Task Characteristics (TC) -> Task-Technology Fit (TTF) | 1.034 | 0.276 | 0.026 | 10.529 | 0.000 | Yes | 0.088 |
| 7 | Technology Characteristics (TEC) -> Task-Technology Fit (TTF) | 1.034 | 0.246 | 0.026 | 9.377 | 0.000 | Yes | 0.070 |
| 8 | Task-Technology Fit (TTF) -> Research Practices (RP) | 1.181 | 0.263 | 0.029 | 8.988 | 0.000 | Yes | 0.073 |
| 9 | Task-Technology Fit (TTF) -> Research Performance (RPE) | 1.254 | -0.139 | 0.029 | 4.846 | 0.000 | Yes | 0.018 |
| 10 | Use Behavior (UB) -> Research Practices (RP) | 1.114 | -0.067 | 0.026 | 2.582 | 0.010 | Yes | 0.005 |
| 11 | Use Behavior (UB) -> Research Performance (RPE) | 1.115 | 0.108 | 0.027 | 4.041 | 0.000 | Yes | 0.012 |
| 12 | Research Practices (RP) -> Research Performance (RPE) | 1.282 | 0.299 | 0.030 | 10.121 | 0.000 | Yes | 0.082 |
| 13 | PER x UB -> RP | 1.114 | 0.012 | 0.026 | 0.446 | 0.656 | No | 0.000 |
| 14 | PER x TTF -> RP | 1.232 | 0.080 | 0.025 | 3.233 | 0.001 | Yes | 0.008 |
| 15 | PER x RP -> RPE | 1.376 | 0.007 | 0.024 | 0.280 | 0.779 | No | 0.000 |

TC ($\beta = 0.276$, $t = 10.529$, $p < 0.001$) and TCh ($\beta = 0.246$, $t = 9.377$, $p < 0.001$) significantly impact TTF, which in turn positively influences RP ($\beta = 0.263$, $t = 8.988$, $p < 0.001$) but negatively impacts RPf ($\beta = -0.139$, $t = 4.846$, $p < 0.001$). UB negatively affects RP ($\beta = -0.067$, $t = 2.582$, $p = 0.010$) but positively influences RPf ($\beta = 0.108$, $t = 4.041$, $p < 0.001$). Finally, RP strongly influence RPf ($\beta = 0.299$, $t = 10.121$, $p < 0.001$).

## 6. Conclusion

The research demonstrates that PE has a significant influence on BI, suggesting that a higher PE is associated with a larger inclination to utilize technology (Venkatesh et al., 2003). Perceived ease of use has a significant role in influencing user intentions, as shown by the positive influence of EE on BI. This finding aligns with the research of (Venkatesh & Bala, 2008), emphasising the significance of ease of use in moulding UB. SI has a considerable influence on BI, highlighting the importance of social norms in the adoption of technology. FC have a direct influence on the actual use of technology UB, emphasizing the need of having supporting resources. The qualities of a task and how well it aligns with technology may improve RPf. However, the alignment between task and technology can have a detrimental influence on the effectiveness of RPf, suggesting a complicated link between task-technology alignment and results.

## 7. Limitations

The study promotes research technology use but has downsides. Cross-sectional research cannot prove causality; short-term and longitudinal studies are required to capture technology's dynamic influence. Social desirability may skew self-reported data and findings. Objective metrics like usage logs may increase results reliability. The study's focus on academics restricts its generalizability since technology adoption characteristics differ by field and culture, underscoring the need for further research across demographics. The approach ignores technical skills, institutional backing, and moderating factors like age and experience that may explain technology's importance.

The study examines Task-Technology Fit but not task characteristics or technology quality, which are needed to understand how technology affects research outcomes. Diverse samples and expanded methodologies would substantially boost technological understanding and research performance.

## 8. Scope of future research

Future research should adopt longitudinal studies to examine the evolving impacts of technology (specifically the booming AI transpose in research) on research performance, enhancing causal insights. Expanding the sample to diverse fields and cultural contexts would improve generalizability. Incorporating objective data, such as usage analytics, alongside self-reports, can reduce biases. Exploring individual differences like technological skills, motivation, and task-specific characteristics will deepen understanding. Additionally, examining moderating factors such as age, experience, and organizational culture would provide insights into the varied effectiveness of technology adoption strategies, ultimately contributing to a more comprehensive understanding of its role in research contexts.

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