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Technology Adoption in a Decade: A Systematic Review of Key Determinants, Theoretical Frameworks, and Global Trends

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Abstract

This study addresses the increasing complexity of understanding factors influencing technology adoption, particularly in developing countries where emerging technologies evolve rapidly. The research aims to identify and analyze dominant trends, theoretical frameworks, variables, and contextual factors shaping technology adoption over the past decade. Using a systematic literature review (SLR) of 57 Scopus-indexed articles published between 2015 and 2025, data were processed through the PRISMA protocol and analyzed using VOSviewer software and meta-synthesis techniques. The findings reveal that perceived ease of use and perceived usefulness remain the most prevalent determinants, while new psychological, social, and cultural dimensions—such as trust, autonomy, technophobia, and social influence—are gaining scholarly attention. Research from developing economies, notably India, Bangladesh, and Indonesia, highlights context-specific challenges and the transformative role of technology in digital ecosystems. The study contributes by proposing an integrative framework synthesizing TAM, TPB, UTAUT, and S-O-R models, offering a comprehensive foundation for future research, policymaking, and practical innovation in technology adoption.

Keyword: technology adoption, systematic literature review, developing countries, digital transformation, behavioral models, emerging technologies.

I. INTRODUCTION

The rapid advancement of technology has profoundly transformed how individuals, organizations, and societies interact with digital innovations. Since the mid-2010s, technology adoption has become one of the most dynamic areas of inquiry across multiple disciplines, from information systems and behavioral science to economics and public policy. This growing scholarly attention underscores the need to understand the complex interplay of technological, psychological, and contextual factors that shape user behavior in adopting new technologies.

In developing countries, the adoption of emerging technologies such as artificial intelligence (AI), blockchain, mobile banking, and educational technology has gained significant momentum. However, the diffusion process often encounters distinctive challenges related to infrastructure, culture, trust, and digital literacy. These contextual

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nuances make it essential to explore technology adoption through multidimensional lenses that go beyond conventional models focused solely on technical aspects.

Over the past decade, a variety of theoretical frameworks have been employed to explain technology adoption behavior. Prominent among them are the technology acceptance model (TAM) by (Davis, 1989) , theory of planned behavior (TPB) (Ajzen, 1991), unified theory of acceptance and use of technology (UTAUT) (Venkatesh, 2000), and stimulus-organism-response (S–O–R) (Mehrabian & Russell, 1974) frameworks. These models have evolved to incorporate new variables such as trust, social influence, autonomy, and perceived enjoyment, reflecting the interdisciplinary expansion of technology adoption research.

Despite this progress, several challenges persist. Existing studies often lack theoretical integration, resulting in fragmented insights across different contexts and technologies. Moreover, review-based studies—although abundant—have not always adopted systematic and meta-analytic approaches capable of identifying global patterns and theoretical convergence. Consequently, there remains a need to synthesize developments in this domain comprehensively, particularly in the context of developing countries, where technology adoption is closely tied to socio-economic transformation.

Given these research gaps, this study aims to systematically identify, analyze, and synthesize the trends, theoretical frameworks, variables, and contexts influencing technology adoption between 2015 and 2025. The overarching goal is to develop an integrative conceptual framework that bridges multiple theories and provides a holistic understanding applicable to diverse technological settings. This synthesis is expected to contribute both theoretically—by mapping the evolution of adoption models—and practically—by informing policymakers, industry leaders, and researchers seeking to foster inclusive digital transformation.

II. LITERATURE REVIEW

The advancement of technology and its adoption has been at the forefront of research across various disciplines since early 2016, highlighting the growing importance of understanding the factors that shape user behavior in embracing digital innovation. Over time, scholars have drawn on a range of theoretical models to explain the technology adoption process more comprehensively, including the technology acceptance model (TAM), the theory of planned behavior (TPB), and the stimulus-organism-response (S-O-R) framework (Oliveira et al., 2016; Zhang et al., 2024; and Yadav et al., 2025). For instance, an early study by Oliveira et al. (2016) in Portugal explored the drivers behind users' intention to adopt mobile payments. This line of inquiry was later extended by Zhang et al. (2024) in Taiwan, who examined technology-based learning and assessment in the education sector.

Subsequent research has expanded across diverse contexts and countries, ranging from the adoption of green technologies in Nigeria (Buba et al., 2022), to the use of chatbots in India (Dhiman & Jamwal, 2023), and the integration of blockchain and AI technologies across various global sectors (Khan et al., 2024; Wang et al., 2025). Notably, in 2025, interest in technologies such as ChatGPT and AI has surged, signaling a paradigm shift in technology adoption studies toward deeper social and cultural dimensions (Tummalapenta et al., 2024; Al-Mamary & Abubakar, 2025). Recent studies have also moved beyond purely technological factors to explore psychological and social dynamics—for example, the application of the COM-B model in mental health services (Cecil et al., 2025) and user behavior in ridesharing platforms in Pakistan (Shah & Hisashi, 2025). Collectively, this evolving body of literature reflects a dynamic and multidimensional understanding of technology adoption, enriched by diverse contextual, cultural, and theoretical perspectives that continue to shape digital-era scholarship (Kuberkar & Singhal, 2021).

Over the past decade, there has been a notable shift in how scholars approach the study of technology adoption. This evolution marks a transition from traditional models that focused primarily on technical factors and individual perceptions (Oliveira et al., 2016; Hu et al., 2019) toward more complex frameworks that incorporate psychological, social, and contextual dimensions (Al-Mamary & Abubakar, 2025; Wang et al., 2020). Early studies predominantly emphasized technical determinants such as perceived usefulness, perceived ease of use, and security as the key drivers in technology acceptance models (Oliveira et al., 2016; Payal et al., 2024). However, more recent trends point to a growing recognition of broader psychological and social factors—such as autonomy, relatedness, and trust—as essential components in understanding user adoption behavior (Wang et al., 2020; Al-Mamary & Abubakar, 2025; and Wang et al., 2025).

In addition, recent approaches have increasingly viewed technology adoption as the result of interactions between individual factors and the broader social and cultural environment—an angle that was often overlooked in earlier models (Kavaarpuo et al., 2025; Yadav et al., 2025). For instance, emerging studies have found that emotional and psychological factors such as technophobia and frustration with unmet psychological needs can significantly influence adoption intentions, suggesting that these dimensions are just as critical as rational considerations (Iskender et al., 2024; Daruwala, 2025). Furthermore, the role of social media and other digital platforms is gaining attention as a moderating factor that can either facilitate or hinder the adoption process, as seen in studies related to biogas and fintech technologies (Wang et al., 2020; Liu et al., 2023). This paradigm shift is prompting both researchers and practitioners to embrace multidisciplinary perspectives—drawing from psychology, sociology, and technology studies—to better grasp the complex dynamics of adoption in the digital age (Kuberkar & Singhal, 2021; Dhiman & Jamwal, 2023). As a result, this evolving framework not only broadens the range of variables considered in adoption models but also enhances the relevance of holistic analytical tools for addressing today's technological opportunities and challenges.

In the literature on technology adoption, review-based studies have played a vital role in identifying research trends and understanding the evolving dynamics of the field. Over the past decade, these studies have consolidated findings from various empirical and conceptual works, providing an overarching view of the key factors influencing technology adoption, such as perceived benefits, barriers, and social influences (Ramlawati et al., 2022). Review methodologies enable researchers to examine the consistency of findings across different contexts and geographic regions, while also highlighting inconsistencies that offer opportunities for further investigation. A major strength of this approach lies in its ability to reveal gaps and limitations in prior research, including the lack of comprehensive contextual approaches and weaknesses in research methodology. Over time, recent studies have shown a shift from descriptive analyses to more structured approaches, such as meta-analyses and systematic reviews, which aim to produce more robust evidence and strategic recommendations for advancing technology adoption. However, despite their usefulness, many review studies continue to face challenges such as study heterogeneity, divergent theoretical frameworks, and limited quantitative data to support comprehensive analysis. Therefore, improving methodological standards and analytical frameworks will be essential for enhancing the strength and reliability of future review-based research.

The scope and objectives of this systematic literature review (SLR) are to identify, analyze, and synthesize previous studies related to the factors influencing technology adoption across various fields, countries, and cultural contexts. Specifically, this review aims to uncover patterns, theories, models, and key variables that drive adoption behavior, including psychological, social, economic, and contextual dimensions that have not been comprehensively explored in existing literature. Additionally, the study is oriented toward developing an integrative and multidimensional conceptual framework that brings together models such as TAM, TPB, and digital ecosystem theories into a cohesive structure. The overarching goal of this research is to provide a comprehensive overview of current trends, research gaps, and innovation opportunities, thereby offering meaningful contributions to both the theoretical development of technology adoption and practical strategies for industry stakeholders and policymakers. The findings of this review are expected to enrich the literature, support evidence-based decision-making, and encourage further investigation into underexplored and emerging aspects of technology adoption in today's digital era.

III. RESEARCH METHODOLOGY

This study follows the preferred reporting items for systematic reviews and meta-analyses (PRISMA) guidelines established by (Moher et al., 2009). PRISMA provides an internationally recognized framework to improve transparency, quality, and consistency in systematic review and meta-analysis reporting. Prior studies support the application of this guideline, emphasizing its value in enhancing the validity and reliability of literature reviews (Panic et al., 2013; Ter Huurne et al., 2017; and Siddaway et al., 2019).

3.1. Methodological Steps

3.1.1. Identification of articles via database search

The review began with an identification phase, using specific keywords such as "technology adoption" and "use intention" to ensure article relevance to the research topic. Scopus was selected as the primary database due to its reputation for providing high-quality scientific publications and its rigorous indexing standards (Bergman, 2012; Rocha & Barroso, 2022). Compared to alternatives like Google Scholar—which often returns duplicate results, includes multiple versions of the same article, and occasionally indexes content from predatory journals—Scopus offers more precise and validated search results.

The initial search in Scopus using the selected keywords yielded a total of 114 articles. After the identification stage, a preliminary screening process was conducted based on the inclusion and exclusion criteria. This process involved removing duplicates (0 articles), excluding irrelevant publications outside the 2015–2025 range (14 articles), and eliminating 12 articles published in Q1–Q4 journals that did not meet the established criteria. Although these 12 studies were published in reputable outlets, they were excluded for several reasons. Most of them lacked direct relevance to the topic of technology adoption from managerial, behavioral, or policy-oriented perspectives. Some did not employ established theoretical frameworks such as TAM, UTAUT, DOI, or S–O–R, while others demonstrated insufficient methodological rigor, either empirically or systematically. A number of articles focused primarily on technical or engineering-specific aspects of technology without addressing behavioral or organizational implications. In addition, several studies were highly localized case analyses with limited generalizability, providing little contribution to understanding broader national or global trends. Consequently, despite their academic credibility, these articles were excluded from the final dataset because they did not align conceptually or methodologically with the objectives of this systematic review.

3.1.2. Screening and selection process

The remaining 88 articles were then screened for title and abstract relevance. No articles were excluded at this stage due to inadequate abstracts or irrelevance (0 articles). However, 33 articles could not be accessed or retrieved from alternative sources and were thus excluded from further analysis.

A total of 55 articles met the screening criteria and were selected for in-depth evaluation. In addition to these, two articles from other credible and peer-reviewed sources were deliberately added to enrich the dataset. The inclusion of these two articles was not arbitrary but driven by their unique contribution to addressing conceptual and contextual gaps that were underrepresented in the Scopus-based corpus. Specifically, both articles provided in-depth discussions on technology adoption in developing-country contexts, with one emphasizing the socio-cultural dimensions of digital transformation and the other offering a cross-disciplinary synthesis that integrates behavioral, managerial, and policy-oriented perspectives. These characteristics were particularly relevant to the aims of this review, as they expanded the analytical scope beyond the primarily technical and quantitative focus of the Scopus dataset. Their addition therefore ensured a more comprehensive and balanced understanding of the global discourse on technology adoption, while also enhancing the theoretical depth, contextual diversity, and representativeness of the final sample. As a result, the final dataset consisted of 57 research articles selected for comprehensive review.

3.2. Inclusion and article quality

The total number of articles meeting the inclusion criteria at the final PRISMA stage was 55, with 2 supplementary studies added, bringing the total to 57. These studies were deemed eligible based on their relevance and methodological rigor. Figure 1 illustrates the PRISMA flow diagram, showing the detailed progression of article identification, screening, and inclusion stages.

3.2.1. Data analysis

The selected articles were analyzed qualitatively using thematic analysis. This step, performed after the PRISMA protocol was completed, ensured that data interpretation was systematic, enabling the identification of core themes, interconnections among themes, and relevant patterns aligned with the study's focus. The thematic analysis was supported by the Watase Uake System, which facilitated the organization and management of extracted data. The keyword query used in Scopus included: technology AND adoption AND use AND intention, applied across article titles, abstracts, and keywords.

The outcome of this search is visualized in the PRISMA diagram presented in Figure 1.

Insert Figure 1 and 2 here.

Subsequently, VOSviewer software (Van Eck & Waltman, 2009) was utilized to construct and visualize bibliometric networks, including keyword co-occurrence mapping and citation analysis. This bibliometric method is a widely used, open-access analytical technique across various scientific disciplines. In this study, VOSviewer supported the development of both keyword co-occurrence networks and citation linkages (Martins et al., 2024). The entire analytical process was further enhanced by a meta-synthesis approach, which integrated findings from relevant studies to provide a comprehensive understanding of the evolving discourse on technology adoption.

Figure 1
PRISMA Literature Review Results Using the Keywords 'Technology Adoption' and 'Use Intention'

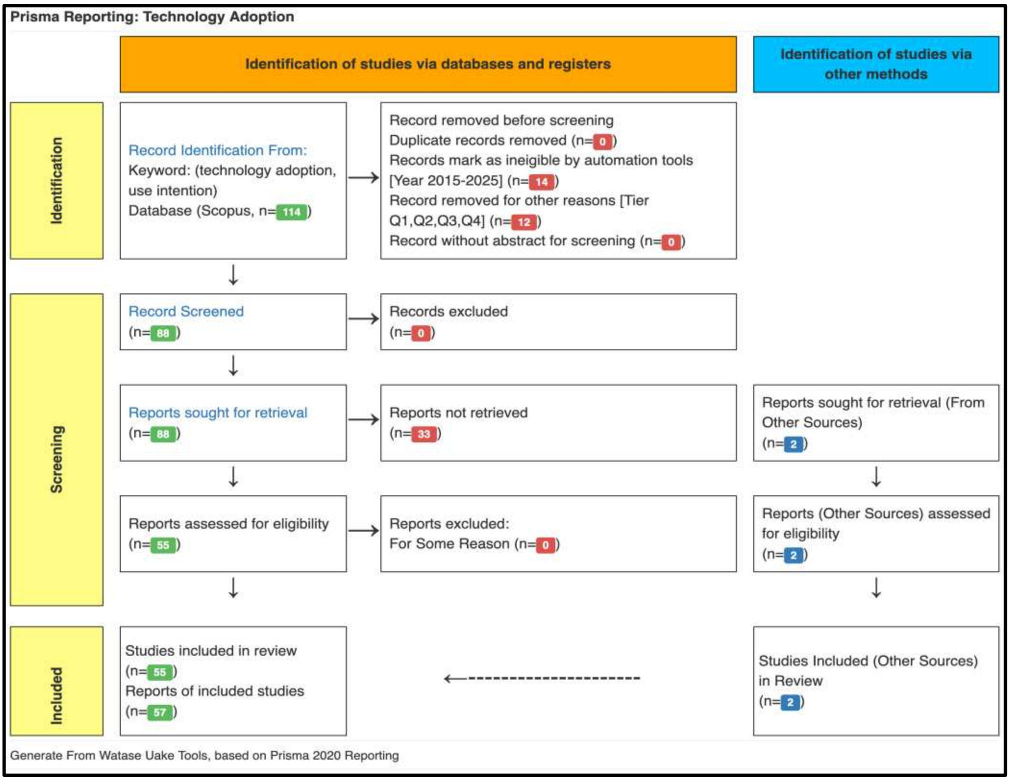
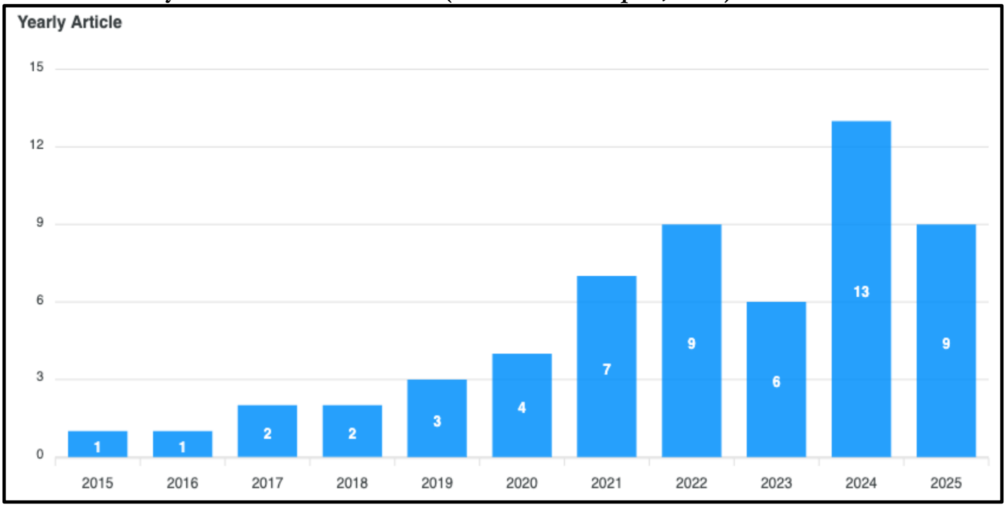


Figure 2
Publications by Year from 2015 to 2025 (Basis Data Scopus, 2025)



A time-series approach was also applied to illustrate the temporal dynamics of publication trends, while qualitative descriptive analysis was used to map how research focus areas have shifted over time. By combining numerical and thematic analyses, this approach enabled not only the presentation of publication quantity but also a deeper exploration of the context and intellectual direction of research developments in the field.

IV. RESULT AND DISCUSSION

This section presents a comprehensive bibliometric analysis aimed at mapping the landscape of existing studies on technology adoption and user intention. It offers insights into the evolution, distribution, and thematic focus of the literature.

4.1. Result

4.1.1. Analyze research output variables trends and country finding

The analysis of variables presented in Table 1 reveals a prevailing trend in academic publications, which tend to focus on core variables directly related to user perceptions and intentions toward technology—most notably, perceived ease of use and perceived usefulness. These two variables emerged as the most dominant, each appearing in five studies from various countries (Davis, 1989; Venkatesh, 2000). This finding reinforces the notion that in the development of technology adoption theories, users' perceived ease and perceived benefits continue to serve as foundational elements. These variables are interrelated and exhibit a direct relationship with behavioral intention and actual adoption (Ajzen, 2011), a pattern that aligns consistently with the technology–behavior model.

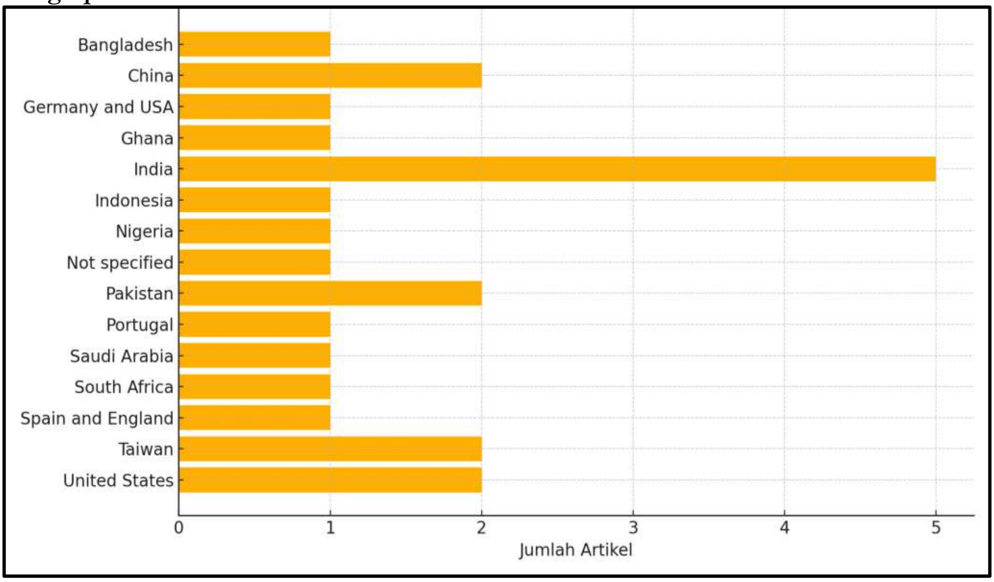
Table 1
Detailed Table of Variables and Countries Represented in the Reviewed Studies

No.	Variables	Country	Total
1	Perceived Ease of Use	India; Pakistan; Spain and England; Indonesia	5
2	Perceived Usefulness	India; Pakistan; Spain and England; Indonesia	5
3	Behavioral Intention	Pakistan; India; Spain and England	3
4	Attitude	India	2
5	Perceived Autonomy	India; Saudi Arabia	2
6	Perceived Competence	India; Saudi Arabia	2
7	Perceived Relatedness	India; Saudi Arabia	2
8	Social Influence	India	2
9	Actual Adoption	Ghana	1
10	Adoption Intention (E-tax and E-marketplace)	Indonesia	1
11	Affinity for Technology Interaction	Germany and USA	1
12	Attitude Towards Use	Pakistan	1
13	Brand Active Engagement	India	1
14	Brand Active Engagement in Metaverse	India	1
15	Brand Attachment	India	1
16	Brand Attachment in Metaverse	India	1
17	Brand Knowledge	India	1
18	Brand Knowledge in Metaverse	India	1
19	Brand Trust	India	1
20	Brand Trust in Metaverse	India	1

In addition, variables related to usage intention—such as behavioral intention and adoption intention—also appear prominently, reflecting a strong research focus on predicting the extent of technology adoption across various contexts, from e-tax systems to marketplace platforms (Ajzen, 2012). These variables are often supported by intermediary factors such as attitude, perceived autonomy, and social influence, highlighting the psychological and social dimensions involved in technology-related decision-making processes (Venkatesh et al., 2003). Sub-variables like trust, credibility, and cognitive readiness further underscore the critical role of user confidence and preparedness—factors that have been empirically shown to strengthen technology adoption models across different regions (Kim & Shin, 2015).

Figure 3

Geographical Distribution of Reviewed Articles



Regionally, out of the 57 articles reviewed, only 23 explicitly identified the countries in which the studies were conducted. A clear trend emerges, reflecting varied thematic priorities across regions. Studies from India tend to focus on variables related to brand engagement and brand attachment, particularly in the context of the metaverse and digital branding, indicating growing interest in how digital environments shape user influence and identity (Huang & Rust, 2021). Meanwhile, in Western countries such as Germany and the United States, variables such as creativity, environmental awareness, and learning intentions dominate, reflecting an emphasis on innovation and sustainability—aligning with global efforts to promote environmentally friendly and forward-thinking technologies (UNEP, 2002). These variables suggest that research in these regions places greater emphasis on user competence development and sustainable adoption strategies. Many of these variables contribute to the evolution of holistic and interdisciplinary models for understanding technology adoption and use, revealing a global research priority to address challenges related to trust, readiness, and user experience. Variables such as perceived risk, technophobia, and sociotechnical blindness illustrate increased awareness of psychological barriers, opening the door to research that integrates psychological and technological perspectives (Venkatesh & Bala, 2008). Overall, this pattern underscores the need for future studies to consider these factors as part of efforts to foster more inclusive and responsible technology adoption (Rogers et al., 2014).

4.1.2. Context classification

The analysis of the research context areas, as presented in Table 2, reveals that studies on technology adoption have been conducted across a wide and diverse range of geographic regions and application domains. Generally, the research contexts have been distributed across various countries, including Bangladesh, Taiwan, India, Portugal, Ghana, Indonesia, Saudi Arabia, the United States, Pakistan, Nigeria, China, Germany, and Spain. This widespread distribution indicates that technology adoption is recognized as a universal phenomenon, relevant across different cultural and economic environments (Oliveira et al., 2016; Payal et al., 2024; Putro & Takahashi, 2024; Zhang et al., 2024; Al-Mamary & Abubakar, 2025; Kavaarpuo et al., 2025; and Sarker et al., 2025).

Insert Table 2 here.

Based on the table presented, it can be observed that the geographical distribution of research locations in the literature review on technology adoption is relatively diverse, yet certain patterns can be identified. The most frequently studied locations are developing countries, such as Bangladesh (Sarker et al., 2025), India (Kuberkar & Singhal, 2021; Dhiman & Jamwal, 2023; Payal et al., 2024; Putro & Takahashi, 2024; and Tummalapenta et al., 2024), Ghana (Kavaarpuo et al., 2025), Nigeria (Buba et al., 2022), and Pakistan (Hu et al., 2019; Wang et al., 2020). This pattern indicates that technology adoption research in developing nations has become a major focus—likely due to the unique challenges and opportunities found in these contexts, such as infrastructure limitations, cultural dynamics, and varying levels of digital literacy (Sarker et al., 2025; Yadav et al., 2025).

In addition to developing countries, several developed nations are also represented in the reviewed studies, including Portugal (Oliveira et al., 2016), Germany and the United States (Cecil et al., 2025), China (Hu et al., 2019; Wang et al., 2025), as well as Spain and the United Kingdom (Daruwala, 2025). Research conducted in developed countries generally focuses on innovative technologies and sectors such as healthcare, finance, and smart home systems, which benefit from more advanced infrastructure and well-established digital ecosystems (Cecil et al., 2025; Wang et al., 2025).

In terms of geographical trends, studies in developing nations have shown a significant surge, positioning these regions as rapidly growing areas of research. This growth is largely driven by the need to better understand local dynamics in the adoption of emerging technologies (Kavaarpuo et al., 2025; Yadav et al., 2025). These findings imply that socioeconomic, cultural, and infrastructural challenges in developing countries play a critical role and warrant deeper exploration to fully grasp global patterns of technology adoption. The relevance of this trend to future challenges is substantial and should not be overlooked.

On the other hand, the challenges and influencing factors in technology adoption are not only shaped by national or regional contexts, but also span across cultural and economic boundaries. Moreover, studies focusing on specific sectors reveal a wide variety of technology application contexts, including education (Oliveira et al., 2016; Zhang et al., 2024; and Wang et al., 2025), mental health (Cecil et al., 2025), manufacturing (Buba et al., 2022), tourism (Obal, 2017; Daruwala, 2025), finance and fintech (Hu et al., 2019; Kuberkar & Singhal, 2021), as well as renewable energy and housing development (Kavaarpuo et al., 2025). This review also highlights that "context" plays a critical role in shaping the process and dynamics of technology adoption, where factors such as security, trust, psychological readiness, and socio-cultural characteristics are adapted based on the specific needs of each sector. Future research opportunities should aim to simultaneously examine contextual, social, economic, and psychological factors in order to develop a more holistic and adaptive framework suited to the continuous evolution of technology. Furthermore, cross-cultural and cross-sectoral studies will be essential for formulating innovative strategies that not only align with technological trends but also take into account the unique characteristics of each setting (Wang et al., 2020; Shah & Hisashi, 2025).

3.1.3. Keyword analysis

The analysis of academic publication trends based on keyword occurrence reveals the dominance of key themes such as technology adoption, technology acceptance models (TAM, UTAUT), and behavioral intentions, which form the foundational pillars of global research on technology adoption. Supporting subthemes include perceived usefulness, perceived risk, trust, and psychological factors such as self-efficacy and attitude—indicating a strong emphasis on human-centric and trust-related dimensions in the adoption process.

Table 3
Frequency of the Keyword 'Technology Adoption'

No.	Keywords	Total	No.	Keywords	Total
1	Technology adoption	17	14	COVID-19	4
2	Adoption intention	13	15	Structural equation modeling	3
3	Technology acceptance model	12	16	Virtual reality	3
4	Adoption	8	17	Technology acceptance	3
5	Behavioral intention	8	18	Blockchain	3
6	Perceived usefulness	7	19	Higher education	3
7	UTAUT	7	20	ChatGPT	3
8	Trust	6	21	Perceived ease of use	1
9	Perceived risk	6	22	E-commerce	1
10	Artificial intelligence	6	23	Behavioral intentions	1
11	Attitude	5	24	Learning intention	1
12	Blockchain technology	5	25	Metaverse	1
13	Information technology	4	26	Performance expectancy	1

The interrelation between these themes illustrates the integration of behavioral and technological theories, enriching the understanding of adoption models across various contexts such as education, healthcare, and e-commerce. Regional trends in countries like Indonesia, Bangladesh, and China highlight a concentrated focus on technology adoption within emerging economies, addressing regional challenges such as the digital divide, sustainable agriculture, and digital public services. Globally, this pattern reflects a core research priority: to foster innovation and overcome psychological and political barriers. The relevance of these themes to future challenges lies in the urgent need for sustainable innovation and contextual adaptation—solutions that can address social, cultural, and infrastructural barriers while leveraging the opportunities brought by digitalization and advanced technologies across sectors.

Insert Figure 4 here.

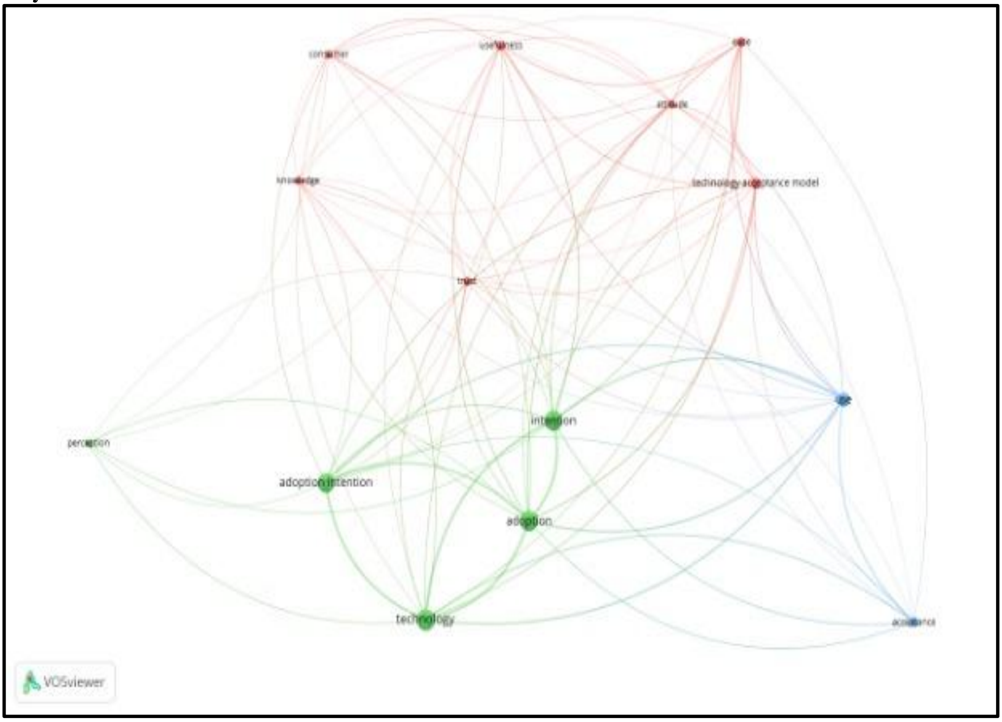
The bibliometric visualization generated using VOSviewer software illustrates the keyword co-occurrence network in literature related to technology adoption. Each node represents a keyword that appears in the analyzed publications, with the size of the node reflecting the frequency of its occurrence. The lines connecting the nodes indicate the strength of association or co-occurrence between keywords within the same article. Different colors represent thematic clusters formed based on the contextual similarity of the terms.

From the visualization, three main clusters were identified.

1) The first cluster (green) focuses on terms such as technology, adoption, adoption intention, intention, and perception, which reflect the core behavioral and psychological aspects of the technology adoption process. Intention and adoption intention appear as central nodes, indicating that intention is a key variable in explaining adoption behavior.

2) The second cluster (red) includes terms like technology acceptance model, usefulness, attitude, trust, consumer, and knowledge. This cluster emphasizes the theoretical foundations of technology adoption, particularly referencing classical models such as TAM and UTAUT, while also highlighting a growing focus on psychological aspects such as trust and perceived usefulness.
3) The third cluster (blue) is dominated by keywords such as use and acceptance, representing the final outcome of adoption intention—actual usage and acceptance of the technology.

Figure 4
Keyword Network Visualization

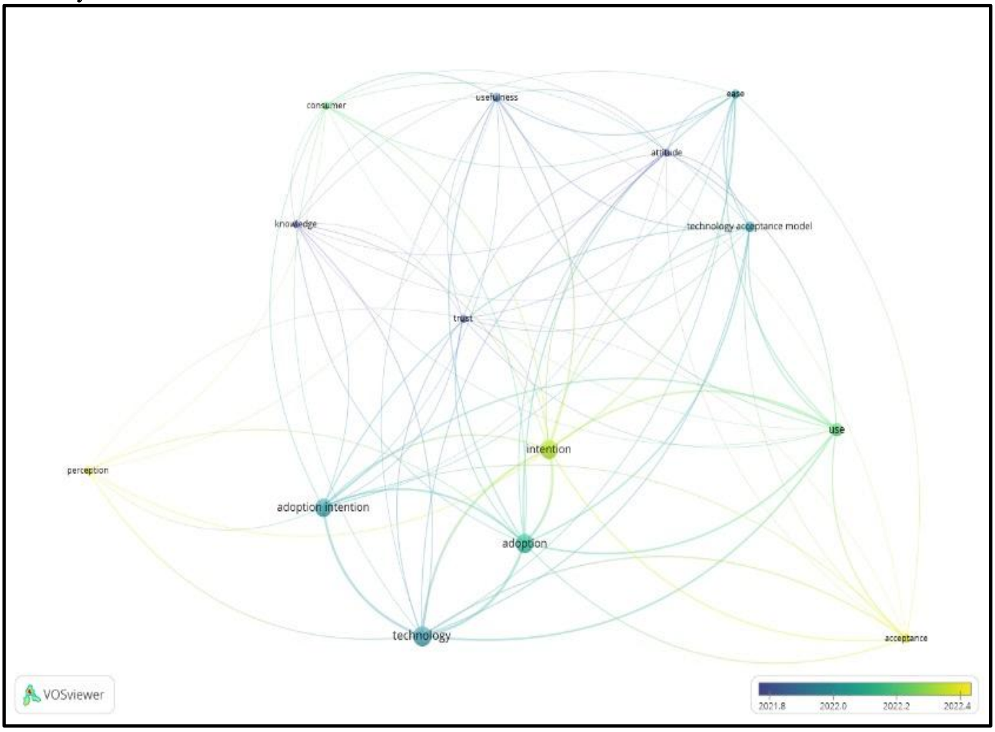


Interestingly, the keyword use serves as a significant bridge between the green and red clusters, indicating that actual usage is the convergence point between users' intention and attitudinal or belief-based factors toward technology. The strong link between trust, usefulness, and adoption intention further reinforces the importance of both affective and cognitive dimensions in technology adoption decision-making.

Insert Figure 5 here.

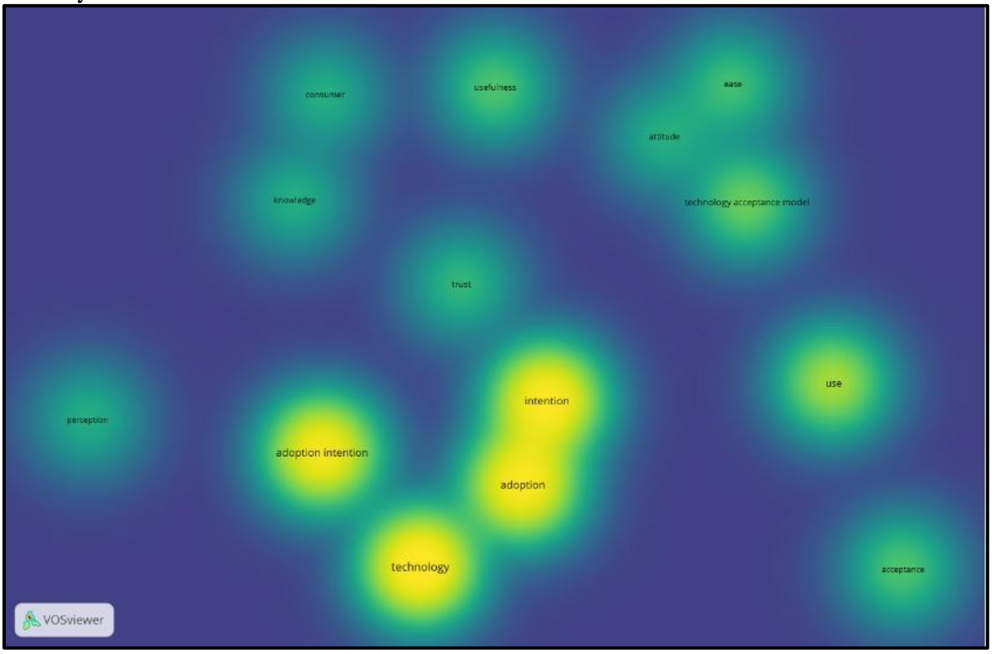
Overall, this visualization suggests that the literature on technology adoption remains heavily influenced by classical theoretical frameworks but is beginning to evolve by incorporating more contextual and emotional variables. The bibliometric map can also be utilized to identify research gaps, such as the limited exploration of cultural factors, regulatory influences, or specific sectors like education and healthcare.

Figure 5
Overlay Visualization



Thus, the results of this bibliometric analysis serve as a valuable reference for developing integrative and interdisciplinary models aimed at understanding the complex dynamics of technology adoption across diverse contexts.

Figure 6
Density Visualization



This heatmap visualization illustrates the intensity of keyword occurrences within the reviewed literature. Areas in yellow represent keywords with the highest frequency, while green to blue areas indicate lower frequencies. The image shows that keywords such as "technology", "adoption", "intention", and "adoption intention" appear most frequently in studies on technology adoption, highlighting their centrality in the field. In addition, terms such as "use", "trust", and "perceived usefulness" also appear frequently, suggesting the importance of attitudinal and trust-related factors in understanding user behavior toward technology. Other keywords like "technology acceptance model", "ease", and "attitude" are also active, although not as dominant as the core terms. Meanwhile, keywords such as "consumer", "knowledge", and "perception" appear in less intense areas, indicating lower frequency but continued relevance. Overall, this heatmap reinforces previous findings that research on technology adoption remains heavily centered around classical models such as TAM and UTAUT, with keywords like intention, adoption, and use serving as focal points in the global academic discourse.

4.1.4. Highly cited articles in technology adoption research

This section analyzes the most influential articles in the field of technology adoption based on citation counts. Highly cited articles reflect significant contributions to theoretical development, research direction, and conceptual understanding in this area. Among the dataset, the ten most cited articles collectively account for 2,909 citations, indicating substantial academic impact.

The most cited article is by Oliveira et al. (2016), published in computers in human behavior, which examines the determinants of digital payment adoption and the intention to recommend such technologies. This article alone has received 987 citations, contributing to more than one-third of the total citations from the top ten list. The second most cited paper is by Hu et al. (2019), published in symmetry, which explores fintech service adoption using an extended TAM model and has garnered 352 citations. Other significant contributions include two separate articles by (Adu-Gyamfi et al., 2022) on battery swap technology for electric vehicles, published in renewable and sustainable energy reviews and energy, receiving 114 and 81 citations respectively. Additionally, influential studies have been published in journals such as cyberpsychology, behavior, and social networking, industrial marketing management, and health psychology research, enriching the field across domains including public health, marketing, and energy systems.

Table 4
Highly Cited Article in Technology Adoption

No.	Journal	Tier	Authors	Year	Cites
1	Computers in Human Behavior	Q1	Oliveira, Tiago; Thomas, Manoj; Baptista, Goncalo; Campos, Filipe	2016	987
2	Symmetry	Q3	Hu, Zhongqing; Ding, Shuai; Li, Shizheng; Chen, Luting; Yang, Shanlin	2019	352
3	Renewable and Sustainable Energy Reviews	Q1	Adu-Gyamfi, Gibbson; Song, Huaming; Obuobi, Bright; Nketiah, Emmanuel; Wang, Hong; Cudjoe, Dan	2022	114
4	Cyberpsychology, Behavior, and Social Networking	Q1	Walrave, Michel; Waeterloos, Cato; Ponnet, Koen	2021	111
5	Energy	Q1	Adu-Gyamfi, Gibbson; Song, Huaming; Nketiah, Emmanuel; Obuobi, Bright; Adjei, Mavis; Cudjoe, Dan	2022	81

To be continued Table 4.

No.	Journal	Tier	Authors	Year	Cites
6	Health Psychology Research	Q2	Chau, Ka Yin; Lam, Michael Huen Sum; Cheung, Man Lai; Tso, Ejoe Kar Ho; Flint, Stuart W.; Broom, David R.; Tse, Gary; Lee, Ka Yiu	2019	75
7	Industrial Marketing Management	Q1	Obal, Michael	2017	66
8	International Journal of Environmental Research and Public Health	Q1	Wang, Zanxin; Ali, Saqib; Akbar, Ahsan; Rasool, Farhan	2020	64
9	Renewable and Sustainable Energy Reviews	Q1	Bondio, Steven; Shahnazari, Mahdi; McHugh, Adam	2018	59
10	Foresight	Q3	Dhiman, Neeraj; Jamwal, Mohit	2022	40

Table 4 presents a detailed list of these articles, highlighting variations in geographical context, year of publication, journal tier, and technological focus. These articles serve as foundational references for the theoretical and empirical development of the technology adoption literature—particularly from 2016 onward, a period marked by the rapid acceleration of digital transformation across various sectors.

4.2. Discussion

The results of this review are generally consistent with existing literature on technology adoption, particularly regarding the role of user perception factors and established theoretical models such as TAM and UTAUT. Prior studies have emphasized that perceived ease of use and perceived usefulness remain core indicators for modeling technology adoption intentions and decisions (Davis, 1989; Venkatesh & Davis, 2000). This trend is further supported by research suggesting that psychological factors and individual perceptions are key drivers of technology acceptance (Beck, 1991; Ajzen, 2012).

At the regional level, the findings are especially relevant to studies conducted in developing countries such as India, Indonesia, and Nigeria, which tend to focus on perceptual and attitudinal variables—consistent with research showing that socio-economic and infrastructural challenges influence user perceptions (Kumar & Sharma, 2025; Yadav et al., 2025) . However, this review also highlights a divergence from earlier literature that emphasized external factors such as trust and risk as primary barriers in certain geographic contexts. For example, studies in Pakistan and Nigeria reveal that perceived risk and trust play significant roles in slowing adoption processes—aligning with findings by (McKnight et al., 2020), who stress the importance of trust in fostering user security and confidence.

Moreover, while earlier literature has often posited that internal perceptions outweigh external factors—especially within classical frameworks like TAM (Davis, 1989) and TPB (Ajzen, 1991)—this review demonstrates the growing significance of external and contextual variables in specific regions, highlighting a shift away from purely conservative interpretations. The dominance of quantitative methods observed in this review also aligns with previous studies, which emphasize the reliance on structural modeling techniques such as SEM and PLS-SEM to examine relationships among variables (Oliveira et al., 2016; Yadav et al., 2025).

Notably, this review underscores an emerging trend toward mixed-methods approaches, combining qualitative and quantitative methodologies to offer a more holistic view of technology adoption phenomena (Wang et al., 2025). This contrasts with earlier studies that often regarded quantitative analysis alone as sufficient to validate theoretical models, indicating a methodological divergence and the need for more diverse research approaches. Overall, the review reaffirms global literature emphasizing the importance of perception, attitude, and psychological variables in adoption processes (Litman & Burwell, 2006), but extends this understanding by showing how external and culturally contextual factors are increasingly recognized as enriching the field (Kim & Shin, 2015). Finally, the adoption of more varied methodologies reflects the field's movement toward a multidimensional and context-sensitive understanding of technology adoption—rejecting static theory in favor of adaptive frameworks that evolve with changing environments and user needs (Rogers et al., 2014 & Venkatesh et al., 2016).

While this systematic literature review (SLR) provides meaningful insights, several limitations should be acknowledged to ensure a contextual and accurate interpretation of the findings. First, the review was constrained to publications from 2016 to 2025, potentially excluding recent or emerging trends and innovations beyond that time frame (Creswell & Clark, 2017). Although this range offers a solid representation of the field's development, fast-paced technological shifts—such as advancements in AI, blockchain, and IoT—may not be fully reflected (Shah et al., 2021).

Second, the review focused solely on journal articles published in English and Indonesian, potentially excluding relevant works in other languages or from gray literature, which might provide valuable region-specific insights (Khan et al., 2024). Additionally, the search method and inclusion criteria were geared toward quantitative studies that employed statistical models like SEM and PLS-SEM. As a result, rich qualitative case studies and interdisciplinary approaches were underrepresented—introducing a potential bias toward generalized findings that may overlook nuanced social and cultural dynamics in technology adoption (Yin, 2018; Creswell & Clark, 2019).

Although network analysis and variable mapping offered a comprehensive overview, the complexity of interrelated variables and dynamic external factors may not be fully captured in the selected studies. This limitation may result in a focus on established variables while underrepresenting subtle or innovative contextual factors, such as regulatory environments or cultural-economic differences across regions (Hofstede & Liu, 2020).

Overall, these limitations should be viewed as opportunities for future research. Broader and more inclusive studies are needed—particularly those incorporating qualitative or mixed-methods approaches—to achieve a more complete understanding of technology adoption dynamics across different fields and geographies (Onwuegbuzie et al., 2007). With these considerations in mind, this SLR should be regarded as an important yet partial guide—one that must continue evolving alongside the dynamic and fast-changing nature of this field (Webster & Watson, 2002).

V. CONCLUSION

This systematic literature review concludes that the primary objective of the study was to identify trends, patterns, and research gaps in the domain of technology adoption, while also offering a broad overview of key developments in the field. The review covers a range of analytical dimensions, including theoretical frameworks, research variables, methodologies, geographic focus, and application sectors. The results show a strong dominance of quantitative methods, with theoretical models such as the technology acceptance model (TAM) and unified theory of acceptance and use of technology (UTAUT) serving as foundational approaches in most of the studies. In particular, 18 articles utilized TAM, especially within sectors like e-commerce, banking, and education, consistently highlighting perceived usefulness and perceived ease of use as strong predictors of user intention. Similarly, UTAUT appeared in 14 studies across areas like government digital services and mobile health platforms, emphasizing the role of social influence and facilitating conditions in shaping user behavior.

Other models also contributed valuable perspectives. The diffusion of innovation (DOI) theory, applied in 5 studies, was especially relevant in sectors such as agritech and SME platforms, where innovation attributes like compatibility and relative advantage played crucial roles. Meanwhile, 3 articles drew on the theory of planned behavior (TPB), focusing on contexts such as higher education and smart home technologies, underlining how social norms and perceived behavioral control affect adoption decisions. A few studies (4 articles) adopted mixed or hybrid models, blending frameworks like TAM and UTAUT with sector-specific and contextual variables to better capture real-world complexities. These mixed-method approaches offered a richer and more nuanced understanding of adoption behavior, particularly in fast-evolving fields such as fintech and smart city services.

Despite the increasing diversity of approaches, several methodological limitations persist. A majority of studies still rely heavily on cross-sectional quantitative designs, with limited attention to qualitative insights or interdisciplinary perspectives that could capture deeper behavioral, institutional, or environmental dynamics. This presents a challenge in understanding the full complexity of adoption processes, especially in under-researched regions or sectors with unique sociocultural contexts. Additionally, variables such as regulation, trust, risk perception, and digital literacy remain underexplored across much of the existing literature, leaving space for more holistic and inclusive models in future studies. Addressing these gaps would enhance theoretical robustness while improving the practical relevance of technology adoption research.

Theoretically, this study contributes by reinforcing the continued relevance of behavioral models while advocating for a broader and more adaptive framework that accounts for context-specific variables and external influences. Practically, the findings stress the importance of designing user-centered technology policies that are sensitive to psychological and cultural dimensions. Moving forward, future research should prioritize mixed-methods approaches, comparative cross-sectoral studies, and inclusion of external contextual variables to ensure that technology adoption models evolve in line with the rapidly changing digital landscape. A deeper engagement with qualitative and longitudinal methods could also yield richer insights into the dynamics of adoption over time. Ultimately, this review provides a foundation for advancing more integrated, responsive, and inclusive strategies in technology adoption scholarship.

5.1. Ethical Disclosure

This study is based solely on a systematic review of existing literature and does not involve any primary data collection involving human participants or animals. Therefore, no ethical approval was required. The research was conducted in accordance with standard academic integrity and ethical research practices.

5.2. Conflict of Interests

The authors declare that there is no conflict of interest regarding the publication of this paper. All sources and references used in this study have been properly acknowledged, and there are no financial or personal relationships that could have influenced the outcomes of this research.

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Table 2
Overview of Technology Adoption Studies: Country, Context, Objectives, and Findings

No.	Researchers	Country	Type of Country	Context	Methods	Purpose	Result	Future Recommendation
1	Oliveira et al. (2016)	Portugal	Developed country	University students and alumni	Quantitative	Factors in mobile payment adoption	Compatibility, security, performance expectancy, innovativeness, and social influence influence adoption and recommendation of mobile payment.	Include trust, risk, and experience as mode-rators; explore usability, productivity gains, and perform cross-country comparisons.
2	Obal (2017)	United States	Developed Country	Cloud computing firms	Quantitative	Continuous adoption of disruptive tech	Preadoption trust increases supplier pressure, possibly decreasing satisfaction; search and efficiency motives support continuance.	Compare opinions of managers and subordi-nates; conduct longitu-dinal studies; explore other disruptive tech-nologies.
3	Hu et al. (2019)	China	Developing country	Fintech users in China	Empirical Research	Fintech adoption in China	Trust strongly affects attitude; ease of use and risk do not significantly influence attitude toward Fintech adoption.	Explore psychological factors and risk percep-tions from multiple angles for a deeper understanding of Fintech adoption.
4	Wang et al. (2020)	Pakistan	NA	Biogas tech in rural Pakistan	Quantitative survey	Biogas tech adoption by farmers	Personal norms, awareness, responsibility, concern, consu-mer effectiveness, and social media affect biogas adoption intention; social media moderates relationship.	Research actual biogas use, include other models and variables, explore various media platforms.
5	Buba et al. (2021)	Nigeria	Developing country	Nigerian manufacturing	Survey	Green-IT adoption in manufacturing	Supports behavioral model for Green-IT adoption in manufac-turing.	Test the model across industries and multi-cultural settings.
6	Kuberkar and Singhal (2021)	India	Developing country	Blood bank tech adoption	Quantitative research	Adoption of Blockchain and IoT in blood bank	NA (not provided in original result).	Study real deployment, scalability, system inte-gration, and broader geographic application.

To be continued Table 2.

No.	Researchers	Country	Type of Country	Context	Methods	Purpose	Result	Future Recommendation
7	Dhiman and Jamwal (2022)	India	Developing	Chatbots in tourism	Quantitative	Drivers of chatbot satisfaction and use	Task and technology characteristics affect task-technology fit, influencing user satisfaction and continuance; perceived usefulness is key.	Expand samples, explore other AI tools, and include more constructs like trust and perceived value.
8	Iskender et al. (2022)	United States	Developed country	QR code menus in U.S. restaurants	Quantitative	Behavioral intention toward QR menus	Performance, hygiene, ease of use, trialability, and social influence explain 62% of behavioral intention to adopt QR code menus.	Test the model with different technologies and service settings; consider longitudinal approaches.
9	Liu et al. (2023)	Taiwan	Developed country	NFTs in hotels during COVID-19	Quantitative	Passion and trust in NFT adoption	Technology adoption propensity affects behavior intention through trust; entrepreneurial passion enhances NFT adoption.	Examine different populations and cultures; investigate consumer perspectives and SME experience with tech adoption.
10	Issock et al. (2024)	South Africa	Developing	Millennial tourists and VR	Quantitative	Tourists' intention to adopt VR tech	Curiosity drives enjoyment and flow, which influence VR adoption intention; trust is essential for tourism VR usage.	Target VR users for real adoption rates and explore additional affective outcomes.
11	Khan et al. (2024)	Not specified	Developing country	Blockchain in libraries	Quantitative	Blockchain adoption intention in libraries	Security, privacy, confidentiality, integrity, authenticity, and possession influence trust and blockchain adoption intention.	Include respondent roles, assess financial capacity of institutions, and explore geographical variation in blockchain adoption.
12	Payal et al. (2024)	India	Developing	Metaverse brand experience	SEM	Brand engagement in metaverse and real-world purchases	Metaverse brand engagement impacts real-world purchases; interactivity affects trust, attachment, and knowledge.	Explore cross-platform engagement and include more diverse demographic samples.

To be continued Table 2.

No.	Researchers	Country	Type of Country	Context	Methods	Purpose	Result	Future Recommendation
13	Putro and Takahashi (2024)	Indonesia	Developing country	Entrepreneurs in Yogyakarta	Quantitative	Creativity and entrepreneurial orientation on IT adoption	Creativity influences usefulness and ease of use; entrepreneurial orientation moderates relation-ship with e-tax adoption intention.	Use objective measures for creativity and ori-entation; explore these variables across different cultural and industry contexts.
14	Tummalapenta et al. (2024)	India	Developing	ChatGPT in Indian higher education	Survey-based SEM	Explore determinants of ChatGPT continuance	Perceived usefulness and attitude predict continuance; autonomy, relatedness, social influence, and recognition affect perceived usefulness and ease of use.	Conduct longitudinal and cross-cultural studies, exa-mine individual differences and specific ChatGPT feat-ures, and explore institu-tional support effects.
15	Zhang et al. (2024)	Taiwan	Developing	Secondary science education, TBAs	Latent Class and Multigroup Path	Identify teacher styles in adopting TBAs	Identified three distinct teacher adoption styles (Rich, Selective, Minimalist) with varying belief, attitude, and external norm influences.	Use multiple data sources, increase sam-ple size, and apply longitudinal or mixed methods to track adoption pattern changes.
16	Al-Mamary and Abubakar (2025)	Saudi Arabia	Developing	ChatGPT adoption in Saudi students	Survey	SDT and TPC on ChatGPT adoption	Perceived autonomy and relatedness influence task-technology fit and utilization; competence has no effect.	Investigate broader de-mographics, larger samples, and genera-tional and contextual diversity in AI adoption.
17	Cecil et al. (2025)	Germany and USA	Developed	AI in mental healthcare	Mixed-methods	AI-enabled tools in mental healthcare	Ethical readiness and affinity for technology predict use intention; cognitive and vision readiness in-fluence learning; self-efficacy mixed.	Use interviews, experimental and longitudinal designs, and analyze complex variable interactions.
18	Daruwala (2025)	Spain and England	Developed	Smart Home Tech in Spain and England	Survey research	Smart home tech behavior across cultures	Ease of use and technophobia mediate relationship between needs frustration and adoption; Spanish users more frustrated but show higher adoption intention.	Include biomarkers to measure anxiety, explore more countries, and ana-lyze age-targeted inter-ventions for reducing technophobia.

To be continued Table 2.

No.	Researchers	Country	Type of Country	Context	Methods	Purpose	Result	Future Recommendation
19	Kavaarpuo et al. (2025)	Ghana	Developing	Real estate sector in Ghana	Quantitative	Effect of transaction uncertainties on adoption	Perceived predictability of mar-ket demand is positively related to adoption of nonconventional building materials; other uncertainties have varied effects.	Conduct longitudinal studies to observe adoption changes and assess government policy impact.
20	Sarker et al. (2025)	Bangladesh	Developing country	Rural women in Bangladesh	PLS-SEM	Investigate ICT adoption and women entrepreneurship	Material access, mental access, skill access, usage access, and ICT in microfinance positively affect ICT adoption intention, enhanc-ing women's entrepreneurship ability.	Consider more diverse populations and explore additional factors influ-encing ICT adoption.
21	Shah and Hisashi (2025)	Pakistan	Developing	Ridesharing in Lahore	Survey	Adoption intentions for ridesharing	Usefulness, ease of use, trust, environmental awareness, and innovativeness boost adoption; perceived risk reduces attitude; females less inclined due to safety concerns.	Extend research to other regions and user groups, use larger samples, and analyze regulatory and gender issues.
22	Wang et al. (2025)	China	Developing	AIGC adoption in China	Grounded theory and fsQCA	Causal mechanisms for AIGC adoption	Six configurations for high adoption intention found; core roles include AI use, perceived control, ethics, and attitude.	Expand research across countries and education-al levels, explore voca-tional institutions, and conduct longitudinal studies.
23	Yadav et al. (2025)	India	Developing	AI in Indian higher education	Field survey and SEM	Factors influencing student AI adoption	Social influence is the strongest predictor of attitude; perceived usefulness, ease of use, and credibility impact attitude; moderated by task-tech fit and cost-effectiveness.	Include risk, trialability, and learnability con-structs; conduct com-parative and longi-tudinal studies across cities and countries.