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## Models of use of mobile technologies (devices and applications): a narrative review

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### Axis: Information and Communication Technologies

#### 1 Introduction

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The pervasive integration of smart mobile devices (SMD) and applications (apps) into daily life has fundamentally altered human interaction with information, communication patterns, and knowledge management practices. As noted by Ding et al. (2021), contemporary SMD combine advanced connectivity with computational capabilities, becoming indispensable tools for both personal and professional activities. This technological shift has created new paradigms in Personal Knowledge Management (PKM), defined by Frand and Hixson (1998) as "the set of practices by which individuals organize, access, and process personal information," while simultaneously transforming infocommunication processes - the integration of information and communication in digital environments (Daher Junior & Borges, 2021).

Despite these advancements, significant challenges persist in optimizing mobile technology usage. Liu et al. (2017) highlight the growing complexity of managing personal knowledge in mobile environments, where information overload and fragmented attention are prevalent issues. Concurrently, as Sarker (2019) observes, the variability of user

behaviors across different contexts creates substantial demands for adaptive usage models that can accommodate diverse needs and preferences.

This research addresses three critical gaps identified in current literature:

- The need for comprehensive models that bridge technical functionality with human cognitive processes (De Masi & Wac, 2020).
- The lack of integration between PKM frameworks and mobile technology design principles (Harrison et al., 2013).
- The emerging requirements for context-aware infocommunication systems (Aliannejadi, 2021).

The study employs a narrative literature review (NLR) methodology, following the approach described by Boell and Cecez-Kecmanovic (2014), to systematically examine existing models of mobile technology usage. This method allows for both descriptive analysis and critical synthesis of established themes while identifying theoretical gaps in the field.

This investigation is guided by three research questions:

- What are the predominant models for SMD and app usage in current literature?
- How do these models contribute to effective PKM practices?
- What role do they play in enhancing infocommunication processes?

The significance of this study lies in its potential to inform both academic research and practical applications. For researchers, it provides a synthesized overview of current models and their theoretical foundations. For practitioners, particularly app developers and interface designers, it offers evidence-based insights for creating more effective mobile solutions. As Huang and Chueh (2022) emphasize, understanding usage models is crucial for developing technologies that align with actual user needs rather than presumed behaviors.

## 2 Theoretical Framework

This study is anchored in three interconnected theoretical pillars that inform the analysis of mobile technology usage models: PKM, Infocommunication Theory, and Technology Acceptance Models (TAM). These frameworks collectively provide a robust foundation for understanding how users interact with SMD and apps, as well as the implications for design and usability.

### 2.1. Personal Knowledge Management

PKM encompasses the strategies individuals employ to organize, retrieve, and apply personal information in digital environments (Frاند & Hixson, 1998). Liu et al. (2017) extend this definition by emphasizing the role of big data and context-awareness in modern PKM systems, particularly in mobile ecosystems. Their work demonstrates that effective PKM relies on:

- Personalization: Adaptive interfaces that align with user behavior Sarker et al., (2019)
- Predictive functionality: Algorithms that anticipate information needs (Huang et al., 2012)

- Cognitive load management: Minimizing mental effort in information processing (Harrison et al., 2013)

The integration of PKM principles into mobile technology design has been shown to significantly enhance user efficiency. For instance, Zhang et al. (2020) developed user embeddings based on app usage patterns, creating personalized knowledge management systems that evolve with user behavior.

### 2.2. Infocommunication Theory

Infocommunication bridges information science and digital communication, focusing on how technology mediates knowledge exchange (Daher Junior & Borges, 2021). This framework is particularly relevant for analyzing mobile search unification and contextual recommendations. Key aspects include:

- Context-aware systems: Aliannejadi (2021) highlights how mobile search behaviors differ from desktop paradigms, requiring hybrid recommendation models that incorporate location, time, and activity data.
- Behavioral mining: Sarker (2019) proposes rule-based algorithms that adapt to real-time user contexts, improving communication relevance.
- Quality of Experience (QoE): De Masi and Wac (2020) link infocommunication efficacy to measurable QoE metrics like latency, interface design, and task completion rates.

### 2.3. Technology Acceptance Models

The TAM and its derivatives explain user adoption of mobile technologies through:

- Perceived usefulness and ease of use (Huang & Chueh, 2022)
- Cognitive dissonance in post-adoption behavior (Pinpathomrat, 2015)

- Adaptation Level Theory (ALT): Users' expectations evolve with prolonged use (Pinpathomrat, 2016)
- Stal and Paliwoda-Pękosz (2019) expanded TAM for mobile knowledge platforms, adding constructs like information quality and trust.

#### 2.4. Synthesis of Frameworks

The intersection of these theories reveals critical insights:

- PKM optimizes individual workflows, while infocommunication enhances collective knowledge sharing.
- TAM variants address the "why" of adoption, whereas QoE models (e.g., PACMAD) measure the "how" of sustained engagement (Harrison et al., 2013).
- Contextual gaps persist in generalizing models across cultures and device types (De Masi & Wac, 2020).

### 3 Methodological Procedures

This study employs a qualitative NLR design, following the constructivist approach outlined by Guba and Lincoln (1994), which acknowledges the subjective interpretation of usage models while maintaining rigorous analytical standards. The methodology was implemented in five phases, adapted from Boell and Cecez-Kecmanovic's (2014) hermeneutic framework for literature reviews:

#### 3.1. Research Identification

Two guiding questions structured the inquiry:

1. "What are the predominant models of SMD and app usage in current literature?"
2. "How do these models contribute to PKM and infocommunication processes?"

These questions align with Frand and Hixson's (1998) PKM dimensions and Daher Junior & Borges' (2021) infocommunication principles.

#### 3.2. Search Strategy

The research protocol incorporated:

Databases: Google Scholar (first-page results only) and SciSpace (Typeset.io), selected for their interdisciplinary coverage (PubGenius Inc., 2025)

Search Strings:

- ("usage model" OR "behavior model") AND ("mobile app" OR "smartphone")
- ("PKM" OR "personal knowledge management") AND ("mobile technology")

AI Tools: Microsoft Copilot (2025) for query refinement and NotebookLM (Google, 2025) for corpus analysis

#### 3.3. Study Selection

Inclusion/exclusion criteria were applied.

Inclusion:

- Peer-reviewed articles addressing SMD/app usage models
- Explicit linkage to PKM or infocommunication concepts
- Empirical or theoretical contributions

Exclusion:

- Preprints, patents
- Studies limited to hardware specifications
- Duplicate publications

The final corpus comprised 16 studies after removing 4 excluded documents.

#### 3.4. Data Extraction & Synthesis

A hybrid coding approach was employed:

- Descriptive Coding: Categorizing studies by model type (e.g., predictive, contextual)
- Thematic Analysis: Identifying patterns using NotebookLM's clustering algorithm (Bucio-García, 2025)

Key variables extracted included:

- Model theoretical foundations
- PKM/infocommunication applications
- Validation methodologies
- Reported effect sizes

#### 4 Partial or Final Results

The narrative review of 16 key studies reveals significant insights about how mobile technology usage models enhance PKM and infocommunication. Context-aware behavior modeling emerges as particularly impactful, with approaches like RecencyMiner (Sarker et al., 2019) demonstrating strong capabilities in predicting application usage patterns by analyzing temporal behaviors. These models facilitate more efficient PKM by automatically organizing frequently used tools and reducing the mental effort required for switching between applications. Energy consumption patterns have also proven valuable indicators of knowledge-intensive tasks and communication behaviors, as shown in Ding et al.'s (2021) research.

QoE studies highlight critical usability factors for mobile applications supporting PKM. The PACMAD model (Harrison et al., 2013) identifies cognitive load reduction, task efficiency, and learnability as fundamental design requirements. Research by De Masi and Wac (2020) further demonstrates how technical factors like low battery levels and network latency substantially degrade user experience, emphasizing the need for robust system performance in knowledge management tools.

Technology acceptance research provides important insights into user adoption patterns. Extended TAM reveal that perceived usefulness, information quality, and trust collectively explain a majority of variance in adoption decisions for mobile PKM tools (Stal & Paliwoda-Pękosz, 2019). While reward programs may initially boost usage intention, Huang and Chueh (2022) caution that they may negatively impact sustained engagement with knowledge management practices.

The unification of mobile search functions presents another important advancement. Aliannejadi's (2021) hybrid recommendation system shows substantial improvements in both search accuracy and efficiency compared to traditional approaches, directly benefiting PKM processes. This aligns with broader findings about the importance of personalized, context-sensitive interfaces for effective knowledge work on mobile devices.

Long-term technology utilization patterns reveal important distinctions between initial adoption and continued use. Pinpathomrat's (2016) Technology Utilization Model (TUM) demonstrates that expectation confirmation and habituation effects play crucial roles in sustaining engagement with mobile knowledge tools, suggesting that adoption strategies should differ from retention approaches.

Across these findings, several consistent themes emerge. Behavioral models show particularly strong impacts on PKM effectiveness, while QoE research emphasizes the fundamental importance of usability in design. The predominance of Android-focused studies in the literature does raise questions about generalizability to other platforms. These results collectively advance our understanding of how mobile technologies can better support knowledge management and communication practices, while also identifying important areas for future research and development.

#### 5 Partial or Final Considerations

This narrative review has systematically examined how mobile technology usage models contribute to PKM and infocommunication, synthesizing insights from sixteen key studies. The findings collectively demonstrate that context-aware behavior modeling, QoE optimization, and extended technology acceptance frameworks offer significant potential for enhancing how users interact with SMD and apps.

The reviewed studies reveal that adaptive models like RecencyMiner (Sarker et al., 2019) and energy-based usage patterns (Ding et al.,

2021) provide robust foundations for developing more intuitive and efficient PKM systems. These approaches align with Frand and Hixson's (1998) vision of PKM as a dynamic, user-centered process, particularly through their ability to reduce cognitive load and automate routine organizational tasks. Similarly, the PACMAD model's emphasis on usability factors (Harrison et al., 2013) and Aliannejadi's (2021) work on unified search interfaces demonstrate how thoughtful design can significantly improve infocommunication processes in mobile environments.

However, several limitations temper these positive findings. The overwhelming Android focus in existing research (De Masi & Wac, 2020) raises questions about cross-platform applicability, while the reliance on living lab data may not fully capture real-world usage complexities. These methodological constraints suggest caution when generalizing results across different technological ecosystems or cultural contexts. Additionally, Huang and Chueh's (2022) findings about the potential negative effects of reward systems highlight how well-intentioned design choices might inadvertently undermine long-term PKM goals.

The theoretical implications of this review are twofold. First, it validates the importance of integrating PKM principles (Liu et al., 2017), infocommunication theory (Daher Junior & Borges, 2021), and TAM (Stal & Paliwoda-Pękosz, 2019) into a cohesive framework for understanding mobile technology usage. Second, it identifies critical gaps in current research, particularly regarding iOS user behavior studies and longitudinal investigations of technology utilization patterns beyond initial adoption phases.

For practitioners, these findings offer actionable insights. Mobile application developers should prioritize context-aware personalization features and cognitive load reduction in interface design, while organizational leaders implementing mobile PKM systems should focus on fostering genuine engagement rather than relying solely on incentive structures. The demonstrated

importance of technical factors like battery optimization and network stability (De Masi & Wac, 2020) also underscores the need for robust infrastructure support.

Future research directions should address the identified limitations through more diverse platform studies and ecological validations of laboratory findings. Additionally, emerging opportunities exist to explore how advanced technologies like generative AI might further enhance mobile PKM systems while addressing current privacy and usability concerns. This review establishes a foundation for such investigations while providing a comprehensive overview of the current state of knowledge in this dynamic field.

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