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Exploring Mobility In Computing: A Review Of Models, Performance Metrics, And Emerging Technologies

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Abstract-
This paper presents a comprehensive review of mobility in computing, examining the dynamics of user, device, and service mobility and their impact on modern networked systems. It addresses the central research question of how can computing systems be architected, measured, and optimized to support pervasive mobility in increasingly heterogeneous and dynamic environments? *To explore this, the study analyzes prevalent mobility models, including random, Gauss–Markov, and Levy-Walk, assessing their applicability and limitations across diverse computing scenarios. Key performance metrics, such as latency, throughput, handover rates, and energy consumption, are evaluated to understand mobility's effect on system performance. Emerging technologies—including edge and cloud computing, AI-driven mobility management, and advanced 5G/6G networks—are also examined for enabling adaptive and efficient mobility-aware computing. Findings highlight critical architectural insights, identify gaps in current approaches, and provide implications for designing resilient, efficient, and user-centric mobile systems while outlining directions for future research.*
Keywords: *Mobility models, Performance metrics, Edge computing, Cloud computing, 5G/6G networks, AI-driven mobility, Mobile systems*

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I. Introduction

Mobility in computing is the capability of systems to support users and devices that change location, maintain connectivity, and interact with distributed resources seamlessly. This encompasses classic *mobile computing* (portable devices accessing computation and communication services while in motion) as well as broader contexts in distributed and edge systems where data and services "move" closer to where computation is needed to enhance responsiveness and adaptability (mobile computing definition & characteristics; connectivity and performance considerations). Moreover, modern definitions of mobility extend beyond user devices to include dynamic behaviors of network topologies, service migrations, and resource orchestration in edge-enabled infrastructures such as multi-access edge computing (MEC).

Mobility in Computing could be User mobility which refers to the ability of a user to access network services or applications seamlessly from different locations and terminals while maintaining continuity of service and identity (ETSI, 2006/2012); Device mobility (also called *terminal mobility*) which concerns the capability of a communication device to move across different network attachment points or technologies without losing connectivity and Service mobility which describes the ability of authorized services to follow the user (or be accessible) regardless of changes in the user's location, terminal, or underlying network infrastructure. It ensures that services remain available and consistent as the context changes, supporting continuity across heterogeneous networks and devices.

In networking and mobile systems, these mobility types function together to support seamless connectivity and uninterrupted service experiences. For example, modern *mobility-aware edge computing* frameworks design service placement and migration strategies to account for user and device movement, highlighting the importance of mobility management for future 6G systems (2024).

Mobility manifests in how data is shifted between cloud and edge layers, how services adapt as devices roam, and how networks sustain connectivity in real time. For example, MEC places computational and storage resources near end devices to support latency-sensitive and location-aware applications such as autonomous systems, smart healthcare, and real-time analytics. In wireless communication, mobility performance is a critical metric that reflects the ability of systems to deliver seamless handovers, maintain quality of service, and ensure robust connectivity as nodes travel across heterogeneous networks. In the context of upcoming sixth-generation (6G) networks, mobility targets—such as supporting speeds approaching 1000 km/h and maintaining reliability—push evaluation frameworks to address metrics like handover success rate, outage probabilities, and latency under extreme conditions.

The importance of mobility has grown in tandem with the proliferation of Internet of Things (IoT) devices, mobile cloud ecosystems, and edge/5G/6G infrastructures. The exponential growth of connected sensors and smart devices in IoT demands infrastructure that supports distributed computing and near-real-time decision-making without being bottlenecked by centralized cloud constraints (latency, bandwidth, and scalability). Edge computing—integrated with 5G's high bandwidth and low latency—enables local processing and contextual services for mobile applications, making mobility support a prerequisite for use cases such as autonomous vehicles, industrial automation, and immersive media. As networks evolve toward 6G, performance expectations intensify, requiring innovative metrics and adaptive models to ensure that mobility shifts from a performance limitation to a design enabler for future applications.

In spite of significant advances in mobile computing, edge computing, and next-generation networks, mobility remains a persistent and poorly resolved challenge in the design, modeling, and performance evaluation of modern computing systems. Current mobility models and performance metrics are often limited in scope, failing to accurately represent complex user mobility patterns and to capture the multidimensional demands of heterogeneous environments such as IoT, mobile cloud, and edge computing systems integrated with 5G/6G infrastructures (Lykakis et al., 2025; Singh et al., 2023). Specifically, existing frameworks frequently overlook service continuity, task migration, and dynamic resource allocation under mobility, which are vital for maintaining quality of service in highly mobile contexts (Singh et al., 2023). Moreover, performance evaluation methodologies are typically simulation-centric and lack real-world alignment, especially as networks evolve toward 6G with more demanding key performance indicators like ultra-low latency and scalability (Liu et al., 2025). These gaps hinder both theoretical understanding and practical optimization of mobility-aware systems, underscoring the need for holistic models and metrics that can support emerging technologies and application domains effectively. Without addressing these issues, mobility will remain a limiting constraint in realizing resilient, efficient, and seamless next-generation computing ecosystems.

Despite advances in mobility in computing, research gaps persist. Many existing models and performance evaluation techniques remain rooted in traditional simulations that do not fully capture real-world movement patterns of devices and users, leading to a disconnect between theoretical assessments and practical system behavior. Likewise, ensuring seamless service continuity across distributed edge zones during high-mobility events remains a largely unresolved problem, with current strategies often failing to coordinate resource allocation, handover management, and predictive decision-making in real time. There is also limited consensus on unified performance metrics that span multi-layer systems (cloud, edge, network) and enable comparative benchmarking across technologies such as IoT, MEC, and 6G frameworks. Furthermore, mobility-aware architectures—especially those that dynamically adapt to user behavior and environmental changes—are still nascent, presenting opportunities for research into algorithmic orchestration, AI-driven optimization, and energy-efficient mobility support.

This exploration, therefore, seeks to articulate a cohesive problem statement: how can computing systems be architected, measured, and optimized to support pervasive mobility in increasingly heterogeneous and dynamic environments? Addressing this question demands comprehensive mobility models that reflect real usage, robust performance metrics that align with emerging network capabilities, and cross-disciplinary strategies that integrate edge computing, IoT, and next-generation wireless technologies into a unified mobility-centric computing paradigm.

II. Theoretical Framework

The Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh, Morris, Davis, and Davis, provides a robust framework for understanding user adoption of technological systems. The theory posits that four key constructs—performance expectancy, effort expectancy, social influence, and facilitating conditions—determine users' behavioral intention and actual usage behavior. In the context of mobility computing, UTAUT is particularly useful for evaluating how individuals and organizations adopt mobile systems, applications, and services. It helps researchers assess not only technical efficiency but also user-centered performance metrics such as usability, perceived usefulness, and system acceptance (Venkatesh et al., 2003).

The Mobility Continuum Framework, associated with Kay, conceptualizes mobility as a continuum rather than a binary state. Instead of viewing systems as either fixed or mobile, this framework positions computing environments along a spectrum that includes static, nomadic, mobile, and ubiquitous computing. This perspective is valuable in mobility research because it enables classification of systems based on their adaptability to context, movement, and environmental interaction. It also provides a conceptual basis for evaluating how different architectures support varying degrees of mobility and context awareness (Kay, 1990).

Context Awareness Theory, advanced by Dey and Abowd, emphasizes the ability of computing systems to sense, interpret, and respond to contextual information such as location, time, user activity, and environmental conditions. In mobile computing, context awareness is foundational to adaptive systems that dynamically adjust services based on changing environments. This theory directly informs the development of performance metrics that measure responsiveness, adaptability, and personalization in mobile and ubiquitous systems (Dey & Abowd, 2000).

Actor-Network Theory (ANT), primarily associated with Bruno Latour, offers a socio-technical lens for analyzing mobility in computing. ANT conceptualizes technologies, users, infrastructures, and policies as interconnected actors within a network of relationships. Rather than isolating technical performance from social dynamics, this framework examines how heterogeneous elements co-evolve. In mobility computing, ANT is useful for tracing how devices, wireless infrastructures, user behaviors, and performance standards interact to shape mobile ecosystems (Latour, 2005).

Diffusion of Innovations Theory, proposed by Everett Rogers, explains how new technologies spread across populations over time. The theory identifies five attributes influencing adoption: relative advantage, compatibility, complexity, trialability, and observability. Within mobility computing, this framework supports the evaluation of emerging technologies such as 5G, IoT platforms, and edge computing by linking technical performance improvements to user and organizational adoption patterns. It also provides metrics for assessing innovation penetration and sustainability (Rogers, 2003).

Mobile Systems Performance Modeling, grounded in Queuing Theory and advanced by scholars such as Leonard Kleinrock, provides a mathematical foundation for analyzing mobile network performance. Queuing models and stochastic processes are used to predict latency, throughput, congestion, packet loss, and handoff delays in dynamic environments. This framework is central to evaluating how mobility impacts system efficiency, particularly in heterogeneous and high-density network scenarios (Kleinrock, 1976).

The Capability Approach, originally developed by Amartya Sen and further elaborated by Martha Nussbaum, offers a human-centered framework that can be extended to mobile computing. Rather than focusing solely on technical performance, the capability perspective evaluates how mobility technologies enhance users' freedoms, opportunities, and functional capabilities. In this context, performance is measured not only by speed or reliability but also by how effectively mobile systems expand access to communication, education, economic participation, and digital inclusion (Sen, 1999).

The framework of Multi-Modal Interaction and Embodied Cognition, associated with Paul Dourish and Ben Shneiderman, highlights the embodied and interactive nature of human-computer interaction. Mobile computing is shaped by users' physical movement, perception, and cognitive processes. This perspective supports performance metrics that account for cognitive load, interaction quality, and user experience alongside traditional network metrics. It is particularly relevant for wearable computing, augmented reality, and gesture-based mobile systems (Dourish, 2004; Shneiderman, 1998).

Adaptive Systems and Feedback Control Theory, articulated by Åström and Murray, models mobile systems as dynamic entities that continuously adjust to environmental changes through feedback loops. In mobile networking, adaptive algorithms regulate signal strength, bandwidth allocation, routing, and handoff mechanisms in real time. This framework provides a rigorous basis for designing optimization strategies that maintain system stability and performance in highly dynamic and heterogeneous mobility environments (Åström & Murray, 2010).

Finally, the Layered Network Architecture (OSI/Internet Model), developed by the International Organization for Standardization (ISO) and advanced within the Internet Engineering Task Force (IETF), serves as a structural framework for mobility management. Although not a theory in the strict sense, it provides the architectural basis for understanding how mobility-related functions—such as routing, handoff, and session management—operate across network layers. Performance metrics such as latency, packet loss, jitter, and throughput are analyzed within specific layers, enabling systematic evaluation of mobility mechanisms (Zimmermann, 1980).

III. Mobility Models

Mobility models are mathematical or computational frameworks used to represent the movement patterns of entities—such as users, devices, or vehicles—within a network. These models are essential for designing, simulating, and evaluating the performance of mobile communication systems, including mobile ad hoc networks (MANETs), vehicular networks (VANETs), and emerging 5G/6G infrastructures (Mubiru &

Westerholt, 2024; Loutfi et al., 2024). By modeling how nodes move and interact, mobility models help researchers understand the impact of movement on connectivity, latency, handovers, and overall network performance, making them a critical tool in network planning and evaluation.

Mobility models are commonly classified into several types based on their movement characteristics. Random mobility models include the Random Walk (RW) and Random Waypoint (RWP) models. In the Random Walk model, each node moves in a randomly chosen direction and speed for a defined period before selecting a new direction, producing memoryless and highly unpredictable motion patterns. The Random Waypoint model, on the other hand, involves nodes selecting a random destination and moving toward it at a randomly chosen speed, pausing for a set time before choosing the next destination. This model is widely used for wireless network simulations due to its simplicity and versatility (Ouyang et al., 2018). Temporal-correlated models, such as the Gauss–Markov model, introduce correlation between past and current velocity or direction, producing smoother and more realistic movement patterns. The degree of randomness can be adjusted, making it suitable for pedestrian or vehicular mobility scenarios (Ouyang et al., 2018). Scale-free and long-tailed models, such as Lévy Walk or Lévy Flight, combine many short movements with occasional long jumps, following a power-law distribution. This approach reflects natural human and animal movement patterns and is particularly useful for modeling mobility in urban or large-area networks (Mubiru & Westerholt, 2024).

The applications of mobility models are extensive and vital for mobile network research and planning. They are used to evaluate handover mechanisms in cellular networks, optimize routing protocols in MANETs and VANETs, simulate mobile edge computing environments to predict service availability, and plan network infrastructure to ensure coverage and quality of service (Loutfi et al., 2024). By accurately modeling movement, mobility models enable network designers to predict connectivity patterns, reduce service disruptions, and optimize resource allocation in dynamic environments, ultimately improving network efficiency and user experience.

Mobility models offer structured frameworks to represent user or node movement over time and space, enabling the simulation of behaviors in complex scenarios such as wireless networks and urban environments. They can reproduce key movement characteristics like velocity, direction changes, and pause times, which are essential for evaluating protocols and systems reliant on mobility dynamics (Mobility Model, n.d.). These models also facilitate controlled and repeatable testing of networking protocols, such as Random Waypoint or Gauss–Markov models, without the costs or constraints of real-world deployments. Beyond networking, mobility models have broad applications in traffic management, urban planning, and epidemiology, where simplified representations, such as gravity or radiation models, can help estimate disease spread or population movement patterns (Barbosa, 2018; Sallah, et. al, 2017).

Despite their utility, mobility models have limitations. Simplified models often assume memory-less movement and uniform randomness, failing to capture real human or vehicular movement patterns influenced by social or destination preferences (Mobility Model, n.d.). Trace-based models improve realism but are constrained by data availability, representativeness, and privacy concerns, which may introduce biases if extrapolated beyond the original context. More complex models that incorporate social behavior or multi-scale dynamics increase computational demands and require careful parameter tuning, and validating them against real movement data remains challenging, affecting the reliability of simulations (Campolo, Molinaro & Scellato, 2019}

In terms of applicability, mobility models are widely used in mobile ad hoc, vehicular, and opportunistic networks to assess protocol performance under different movement conditions (Mobility Model, n.d.). In urban planning, models incorporating spatial flows, such as gravity and radiation frameworks, help forecast commuter patterns, traffic loads, and infrastructure needs (Barbosa, et al., 2018). Similarly, in epidemiology and public health, mobility models aid in predicting disease spread in low-data environments, offering approximations where detailed tracking data are unavailable (Sallah, et. al., 2017).

IV. Evaluation Metrics For Mobility In Computing

Mobility in computing environments—such as mobile ad-hoc networks (MANETs), vehicular networks (VANETs), IoT systems, and 5G-enabled edge infrastructures—requires rigorous evaluation using well-defined performance metrics. As user, device, and service mobility increase in complexity, metrics such as latency, throughput, Quality of Service (QoS), energy efficiency, and reliability become critical in assessing system performance and sustainability (European Telecommunications Standards Institute [ETSI], 2022; International Telecommunication Union [ITU], 2020). These metrics help quantify how mobility affects network stability, service continuity, and overall computing efficiency.

Latency is the time delay between a data request and the corresponding response. In mobile computing environments, latency is heavily influenced by handovers, routing dynamics, edge offloading, and network congestion. Ultra-low latency is particularly essential in 5G-enabled applications such as autonomous vehicles, augmented reality, and remote healthcare (International Telecommunication Union [ITU], 2020). In mobility scenarios, frequent topology changes can increase end-to-end delay due to route rediscovery and packet retransmissions (Camp et al., 2002). Multi-access edge computing (MEC) architectures are specifically designed to reduce latency by processing data closer to mobile users (Nencioni et al., 2021).

Throughput measures the rate at which data is successfully delivered over a network, typically expressed in bits per second (bps). Mobility affects throughput due to link breakages, signal fading, and varying node density. Studies in MANET simulations demonstrate that node speed and mobility patterns significantly influence packet delivery rates and throughput stability (Gupta et al., 2013; Rahman et al., 2020). In 5G systems, advanced spectrum management and network slicing aim to maintain high throughput despite dynamic user mobility (ITU, 2020).

Quality of Service (QoS) encompasses a set of performance parameters—including delay, jitter, packet loss, and bandwidth availability—that collectively determine service performance. Mobility introduces variability in QoS due to fluctuating connectivity and handover interruptions. According to ETSI (2022), mobility management mechanisms must ensure session continuity and minimal QoS degradation during transitions between network attachment points. In edge computing environments, adaptive resource allocation strategies are employed to sustain QoS for latency-sensitive and bandwidth-intensive applications (Khan et al., 2019).

Energy efficiency evaluates the amount of computational or communication output achieved per unit of energy consumed. This metric is particularly significant in battery-powered mobile devices and IoT nodes. Mobility increases energy consumption due to repeated route discovery, signal scanning, and handover processes (Gu et al., 2011). Efficient mobility-aware routing protocols and edge offloading mechanisms can reduce unnecessary transmissions and extend device lifetime. In 5G and beyond networks, energy-efficient mobility management is considered a key design objective for sustainable computing systems (Nencioni et al., 2021).

Reliability is the ability of a system to maintain consistent service delivery despite mobility-induced disruptions. It is often measured using packet delivery ratio (PDR), connection stability, and fault tolerance. High mobility scenarios can reduce reliability due to frequent topology changes and network partitions (Camp et al., 2002; Nisar et al., 2014). Emerging 5G architectures integrate redundancy mechanisms, multi-connectivity, and intelligent handover strategies to enhance reliability under dynamic movement conditions (ITU, 2020). Reliability is increasingly critical in mission-critical applications such as smart grids, intelligent transportation systems, and remote industrial automation.

Evaluating mobility in computing requires a structured comparative analysis across diverse movement patterns, network architectures, and computing paradigms. Different mobility scenarios—such as low-speed pedestrian mobility, high-speed vehicular mobility, group mobility, and edge-assisted 5G mobility—introduce varying levels of topology dynamics and connectivity disruptions. As a result, core performance metrics including latency, throughput, Quality of Service (QoS), energy efficiency, and reliability exhibit distinct behaviors depending on node velocity, pause time, density, and the degree of infrastructure support available (Camp et al., 2002; International Telecommunication Union [ITU], 2020). Understanding these variations is essential for designing adaptive mobility-aware computing systems.

In low-speed or pedestrian mobility scenarios, such as Random Walk models or indoor IoT environments, network topology evolves gradually. Because node movement is slow and link breakages are infrequent, route stability tends to remain high. This stability reduces the frequency of route rediscovery processes, thereby lowering end-to-end latency and maintaining relatively stable throughput levels (Camp et al., 2002). Reliability, often measured through packet delivery ratio, is generally higher in such environments due to sustained link connectivity. Energy consumption is moderate because control overhead and retransmissions are limited. However, even in low-mobility contexts, dense IoT deployments may experience QoS degradation caused by channel interference, congestion, and bandwidth constraints rather than mobility itself (Gu et al., 2011).

In contrast, high-speed vehicular mobility, characteristic of Vehicular Ad Hoc Networks (VANETs), introduces rapid topology changes and frequent link disconnections. As node speed increases, routes break more often, triggering repeated route discovery and handover processes. These dynamics lead to increased latency and reduced throughput due to packet loss during transient disconnections. QoS becomes unstable, particularly for delay-sensitive applications such as real-time video streaming or safety messaging. Additionally, energy consumption rises because of frequent signaling, retransmissions, and topology updates. Reliability declines at very high speeds as maintaining stable communication paths becomes increasingly difficult (Nisar et al., 2014). To address these challenges, advanced 5G mobility management mechanisms—such as fast handover, beamforming, and multi-connectivity—are designed to reduce service interruption and enhance continuity under high-mobility conditions (ITU, 2020).

Group mobility scenarios, such as those modeled by the Reference Point Group Mobility (RPGM) model, present a different performance profile. In these cases, nodes move collectively with correlated motion patterns, maintaining relatively stable intra-group links. Compared to random independent movement, group mobility often results in more predictable latency and improved throughput due to reduced route fragmentation. Reliability within the group is typically higher because nodes maintain consistent relative positions. Energy efficiency can also improve when routing protocols exploit group structure to minimize redundant transmissions.

However, communication between different groups may still experience instability if inter-group distances vary significantly. As noted by Camp et al. (2002), group mobility more closely reflects realistic scenarios such as disaster recovery operations or coordinated team movement, leading to more consistent and context-aware performance outcomes.

Edge-assisted mobility in 5G environments integrated with Multi-access Edge Computing (MEC) represents a more advanced paradigm. In such architectures, computation and content delivery are offloaded to edge servers positioned closer to mobile users. This significantly reduces latency by shortening the communication path between user devices and processing resources. Throughput remains high due to optimized spectrum allocation, network slicing, and enhanced radio resource management. QoS improves through dynamic resource orchestration and predictive mobility management. Energy efficiency also increases because mobile devices offload computationally intensive tasks to edge nodes, reducing local processing demands. Reliability is strengthened through redundancy mechanisms, intelligent handover strategies, and distributed service architectures. Surveys on 5G MEC performance consistently show that infrastructure-assisted mobility environments outperform purely ad hoc systems across most key metrics (Nencioni et al., 2021; Khan et al., 2019).

Overall, comparative analysis across mobility scenarios demonstrates that performance degradation is closely tied to mobility intensity and topology volatility in infrastructure-less networks. However, emerging 5G and edge computing architectures decouple mobility from severe performance penalties through intelligent management and distributed processing. Consequently, future mobility evaluation frameworks must integrate networking, computation, and energy considerations holistically to provide accurate cross-scenario performance assessments. This comparative summary is shown in Table1

Table1- comparative summary table

Mobility Scenario	Latency	Throughput	QoS Stability	Energy Efficiency	Reliability
Low-Speed / Pedestrian	Low	Stable	Moderate–High	Moderate	High
High-Speed Vehicular	High	Variable / Reduced	Low	Low	Moderate–Low
Group Mobility	Moderate	Stable	High (intra-group)	High	High (local)
5G + Edge-Assisted	Very Low	High	Very High	High	Very High

V. Trade-Offs And Optimization Challenges In Mobility In Mobile Computing

Mobility in mobile computing environments introduces fundamental trade-offs among latency, throughput, energy efficiency, reliability, and Quality of Service (QoS). As mobile nodes dynamically change their point of attachment across heterogeneous networks—including MANETs, VANETs, IoT systems, and 5G-enabled edge infrastructures—maintaining seamless service continuity becomes increasingly complex. Early mobility modeling studies demonstrated that increased node speed and topology dynamics directly influence routing stability and network performance (Camp et al., 2002). In modern systems, mobility management must also align with ultra-low latency and high-reliability requirements defined under IMT-2020 performance specifications (International Telecommunication Union [ITU], 2020).

One significant trade-off exists between latency and energy efficiency. Reducing end-to-end delay often requires proactive handover mechanisms, frequent topology updates, and continuous signal monitoring. While these strategies minimize service disruption, they increase signaling overhead and energy consumption in battery-powered devices. Conversely, energy-saving strategies such as adaptive sleep scheduling and reduced control messaging conserve power but may increase delay and packet loss. In edge-enabled 5G systems, computation offloading reduces device-side energy usage; however, unstable connectivity can introduce transmission delays and additional overhead (Khan et al., 2019; Nencioni et al., 2021). Thus, optimizing latency without compromising energy sustainability remains a persistent challenge.

A related trade-off occurs between throughput and reliability in high-mobility environments. Higher transmission rates can maximize throughput under stable conditions, yet in highly dynamic topologies—such as vehicular networks—rapid link breakages reduce packet delivery ratios and increase retransmissions. Reliability-enhancing techniques such as multipath routing, redundancy, and acknowledgment-based recovery mechanisms improve packet delivery but consume additional bandwidth and energy, thereby reducing effective throughput (Nisar et al., 2014). Consequently, mobility-aware routing protocols must balance aggressive data transmission with adaptive reliability controls.

Another optimization challenge involves balancing QoS guarantees and scalability. Ensuring strict QoS requirements—bounded latency, minimal jitter, and low packet loss—is difficult in dense or highly mobile environments. As node density increases, the overhead required for topology awareness and coordination grows significantly. While infrastructure-supported systems, particularly those aligned with mobility management standards from the European Telecommunications Standards Institute (ETSI), improve scalability through centralized coordination, ad hoc networks rely on distributed routing mechanisms that may struggle to maintain

QoS consistency (Camp et al., 2002). This creates a trade-off between decentralized flexibility and centralized efficiency.

Handover management also presents a critical optimization dilemma. Fast and seamless handovers reduce service interruption and improve reliability, especially in 5G environments with multi-connectivity features (ITU, 2020). However, predictive mobility algorithms and context-transfer mechanisms require additional computational resources and signaling exchange. Incorrect predictions can trigger unnecessary handovers—often referred to as the "ping-pong effect"—which increase both latency and energy consumption. Designing intelligent, lightweight, and accurate mobility prediction models remains a key research challenge.

Security and privacy further complicate mobility optimization. Strong authentication, encryption, and continuous identity management enhance reliability and protect against attacks during network transitions. However, these mechanisms introduce computational overhead and may increase delay, particularly in resource-constrained mobile devices. Lightweight security protocols reduce overhead but may expose the system to vulnerabilities. Therefore, security mechanisms must be carefully balanced against performance efficiency in mobile computing systems.

From a systems perspective, mobility optimization is inherently a multi-objective problem. Designers must simultaneously minimize latency and energy consumption while maximizing throughput, reliability, and QoS. Traditional single-metric optimization techniques are insufficient in dynamic mobility environments. Instead, multi-objective optimization approaches—such as Pareto-based analysis, adaptive routing heuristics, and AI-driven mobility prediction—are increasingly necessary to balance competing performance requirements (Khan et al., 2019; Nencioni et al., 2021).

In summary, mobility in mobile computing involves continuous negotiation among competing performance objectives. Increased node speed, topology volatility, and service heterogeneity intensify trade-offs across core metrics. Although emerging 5G and edge computing architectures mitigate many mobility-induced disruptions through distributed processing and intelligent orchestration, achieving optimal balance among latency, throughput, energy efficiency, reliability, and security remains an open research challenge.

VI. Emerging Technologies Supporting Mobility

A. Mobile-cloud /Mobile-edge computing (mcc/mec)

Mobile computing has evolved significantly with the integration of cloud and edge computing paradigms, enabling resource-constrained mobile devices to leverage distributed computational and storage infrastructures. Traditional mobile systems were limited by device constraints such as battery capacity, processing power, and storage. Mobile cloud computing (MCC) emerged as a solution by offloading computation and data storage to centralized cloud data centers, thereby extending device capabilities and enabling computation-intensive applications such as augmented reality, real-time analytics, and mobile healthcare (Satyanarayanan, 2017; Dinh et al., 2013).

Mobile cloud computing refers to an architecture in which mobile devices offload computation and storage tasks to remote cloud servers via wireless networks. This model enhances scalability, flexibility, and processing efficiency while reducing device-side resource consumption. MCC improves application performance by leveraging elastic cloud resources, but it also introduces challenges such as increased latency, bandwidth dependency, and potential service disruption due to mobility (Dinh et al., 2013).

Latency remains a primary concern in MCC because data must traverse the core network to reach centralized cloud servers. In high-mobility scenarios, frequent handovers and unstable connectivity may further increase transmission delays. Despite these challenges, MCC provides significant benefits in terms of computational scalability, centralized security management, and large-scale data processing (Satyanarayanan, 2017). However, the physical distance between users and cloud data centers limits its suitability for ultra-low-latency applications required in emerging 5G environments (International Telecommunication Union [ITU], 2020).

To address the latency and bandwidth limitations of Mobile Cloud Computing (MCC), Mobile Edge Computing (MEC)—also referred to as Multi-access Edge Computing—brings computation and storage resources closer to the end users at the network edge. Defined by the European Telecommunications Standards Institute (ETSI), MEC enables application processing at base stations or edge servers, significantly reducing end-to-end delay and improving Quality of Service (European Telecommunications Standards Institute [ETSI], 2022).

Edge computing supports real-time and latency-sensitive applications such as autonomous vehicles, industrial automation, and immersive media services. By minimizing data traversal to centralized clouds, MEC reduces backhaul congestion and enhances energy efficiency on mobile devices through localized offloading. Surveys on 5G-enabled edge computing demonstrate improvements in latency, reliability, and service continuity under high-mobility conditions (Nencioni et al., 2021; Khan et al., 2019).

B. Iot-enabled mobile systems:

The integration of the Internet of Things (IoT) into mobile computing has significantly expanded the scope of mobility-aware systems. IoT-enabled mobile systems consist of interconnected sensors, actuators, wearable devices, vehicles, and smart objects that communicate through wireless networks while supporting dynamic user and device mobility. These systems operate across heterogeneous environments, combining cloud computing, edge computing, and wireless communication technologies to enable real-time data collection, processing, and decision-making (Atzori et al., 2010; Al-Fuqaha et al., 2015). As mobility increases, maintaining seamless connectivity, low latency, and reliable data transmission becomes a central design challenge.

IoT-enabled mobile systems rely heavily on wireless communication protocols such as Wi-Fi, LTE/5G, Bluetooth Low Energy (BLE), ZigBee, and LoRaWAN. Mobility introduces frequent handovers and topology changes, especially in large-scale deployments such as smart cities and intelligent transportation systems. These dynamics affect key performance metrics including latency, throughput, energy efficiency, and reliability. According to Al-Fuqaha et al. (2015), IoT architectures must incorporate adaptive routing, efficient data aggregation, and scalable network management mechanisms to cope with node mobility and intermittent connectivity.

Energy efficiency is a critical consideration in IoT-enabled mobile systems because many devices are battery-powered and resource-constrained. Mobility increases energy consumption due to repeated association, routing updates, and signal scanning processes. Lightweight communication protocols and edge-assisted data processing have been proposed to reduce transmission overhead and extend device lifetime (Satyanarayanan, 2017). Offloading computation to nearby edge servers minimizes the processing burden on mobile IoT nodes while reducing end-to-end latency compared to centralized cloud architectures.

Security and privacy also present significant challenges in IoT-based mobile computing. As devices move across heterogeneous networks, ensuring secure authentication, encryption, and data integrity becomes more complex. The distributed and often resource-constrained nature of IoT devices makes them vulnerable to attacks such as spoofing, eavesdropping, and denial-of-service. Robust identity management and lightweight cryptographic mechanisms are therefore essential to protect mobile IoT ecosystems (Al-Fuqaha et al., 2015).

In smart city environments, IoT-enabled mobility supports applications such as traffic monitoring, environmental sensing, mobile healthcare, and industrial automation. For example, mobile sensors embedded in vehicles collect traffic data and transmit it to edge servers for real-time analytics. Similarly, wearable health devices continuously monitor physiological signals and transmit alerts through mobile networks. These applications demand ultra-reliable low-latency communication (URLLC), as outlined in IMT-2020 specifications (International Telecommunication Union [ITU], 2020), reinforcing the need for edge-supported IoT architectures.

From a systems perspective, IoT-enabled mobile computing represents a convergence of sensing, communication, computation, and mobility management. Future research directions focus on mobility-aware routing protocols, AI-driven predictive analytics, distributed edge intelligence, and sustainable energy management strategies. The combination of IoT and mobile computing is thus enabling scalable, context-aware, and adaptive systems capable of operating efficiently in highly dynamic environments.

C. Ai/ml-driven mobility optimization

Artificial intelligence (AI) and machine learning (ML) techniques have increasingly been applied to optimize mobility in computing systems, addressing challenges such as dynamic topology changes, unpredictable user behavior, and heterogeneous network conditions. Traditional mobility management approaches often rely on static routing protocols or heuristic-based handover mechanisms, which are insufficient to handle the complexity and scale of modern mobile networks. AI/ML-driven solutions provide predictive, adaptive, and context-aware capabilities that enhance network performance across latency, throughput, reliability, and energy efficiency metrics (Zhang et al., 2020; Taleb et al., 2017).

D. Predictive mobility and routing optimization

AI and ML models can predict future node locations and network states based on historical mobility patterns, enabling proactive handovers, resource allocation, and route selection. For instance, supervised learning algorithms, such as recurrent neural networks (RNNs) or long short-term memory (LSTM) models, can forecast vehicular or pedestrian mobility patterns, reducing route breakages and minimizing end-to-end latency (Huang et al., 2021). Similarly, reinforcement learning (RL) approaches enable mobile devices to learn optimal routing and transmission policies in dynamic environments by interacting with the network and receiving feedback on performance outcomes, such as throughput and packet delivery ratio (Zhang et al., 2020).

E. Resource allocation and edge-assisted offloading

In edge-assisted mobile computing, AI/ML algorithms can dynamically optimize computation offloading decisions by considering network conditions, device capabilities, and task requirements. For example, deep reinforcement learning (DRL) can balance the trade-offs between offloading computation to edge servers or local execution, minimizing energy consumption while satisfying latency constraints (Khan et al., 2019). Predictive analytics also facilitate adaptive resource provisioning, such as bandwidth allocation, server load balancing, and multi-connectivity management, to ensure seamless service delivery in high-mobility scenarios (Nencioni et al., 2021).

F. Anomaly detection and reliability enhancement

Machine learning models contribute to reliability and security in mobility-aware computing by detecting anomalies caused by unexpected mobility patterns, link failures, or malicious activity. Unsupervised learning techniques, such as clustering and autoencoders, can identify deviations from normal network behavior, enabling proactive mitigation measures. Integrating AI/ML-driven anomaly detection with mobility management enhances system robustness, particularly in IoT-enabled mobile environments where device heterogeneity and mobility increase vulnerability to disruptions (Al-Fuqaha et al., 2015).

G. 5g/6g network integration

The integration of 5G and emerging 6G networks into mobile computing represents a transformative step in supporting high-mobility, low-latency, and ultra-reliable applications. Next-generation cellular networks provide enhanced bandwidth, massive device connectivity, and advanced network slicing capabilities, enabling mobile computing systems to meet stringent Quality of Service (QoS) requirements in dynamic environments (Taleb et al., 2017; Saad et al., 2019). By combining 5G/6G with edge computing and AI-driven mobility management, mobile devices can achieve seamless service continuity, optimized resource utilization, and predictive mobility support.

5G networks are designed to support ultra-reliable low-latency communications (URLLC), enhanced mobile broadband (eMBB), and massive machine-type communications (mMTC) (International Telecommunication Union [ITU], 2020). In mobility-aware computing, 5G facilitates rapid handovers, reduced end-to-end latency, and high throughput even in dense or high-speed vehicular scenarios. Multi-access edge computing (MEC), a core component of 5G architecture, places computation and storage resources closer to end users, allowing latency-sensitive applications such as autonomous vehicles, augmented reality, and mobile healthcare to operate efficiently (Nencioni et al., 2021; Khan et al., 2019). AI/ML algorithms can leverage 5G's network slicing and real-time telemetry to optimize mobility-aware routing, load balancing, and task offloading decisions.

6G networks, currently in research and early prototyping stages, aim to deliver terabit-per-second peak data rates, sub-millisecond latency, pervasive AI-native infrastructure, and integrated sensing-communication capabilities (Saad et al., 2019; Zhang et al., 2022). For mobile computing, 6G promises to enhance predictive mobility management by providing ultra-accurate location awareness, intelligent spectrum allocation, and network orchestration across heterogeneous devices and edge nodes. 6G is expected to fully integrate AI/ML-driven mobility optimization, IoT, and edge/cloud computing to deliver adaptive, context-aware services for highly mobile users, such as drone fleets, connected vehicles, and large-scale IoT deployments.

Integrating 5G/6G networks into mobile computing improves end-to-end performance metrics such as latency, throughput, energy efficiency, and reliability. For example, predictive handover algorithms combined with multi-connectivity in 5G enable seamless service continuity in high-speed vehicular networks (Taleb et al., 2017). In 6G, AI-assisted resource orchestration can proactively allocate spectrum and edge computing resources based on mobility patterns and application requirements (Zhang et al., 2022).

However, challenges remain, including the complexity of managing heterogeneous devices, ultra-dense deployments, frequent handovers, and multi-layered resource allocation. Security and privacy considerations are amplified due to the massive number of connected devices and frequent mobility events. Efficient algorithms that combine AI, edge computing, and 5G/6G capabilities are essential to optimize performance while maintaining energy efficiency and secure operation in highly dynamic mobile computing environments.

In summary, 5G and future 6G networks are critical enablers for mobility in computing, providing low-latency, high-throughput, and reliable connectivity. Their integration with AI/ML, edge computing, and IoT forms the foundation of next-generation mobility-aware computing systems, supporting seamless and adaptive services in increasingly dynamic and heterogeneous network environments.

VII. Related Works

Camp, Boleng, and Davies (2002) conducted a comprehensive survey of mobility models for ad hoc network research, classifying both entity and group mobility models commonly used in MANET simulations. While the study provides a solid foundation for understanding mobility modeling in ad hoc networks, it primarily focuses on traditional MANET models and does not integrate modern performance metrics or emerging technologies such as 5G and edge computing. Building on this, Rahman, Alam, and Z. Rahman (2020) investigated the effects of mobility metrics in mobile ad hoc networks using NS-2 simulations to evaluate how parameters like relative speed, node degree, and network partitions affect performance metrics such as packet delivery ratio and delay. Their analysis, however, is limited to MANET settings and does not consider broader computing paradigms beyond routing protocol performance.

Gu, Prasad, and Niemegeers (2011) explored mobility modeling for personal networks through an analytical review, focusing on stability and node clustering models. Although this early work offers insights into mobility behaviors, it provides limited evaluation of performance metrics relevant to modern computing systems, including edge and IoT environments. Similarly, Dhurandher, Sharma, and Woungang (2014) performed a simulation-based comparison of history-based prediction routing under different mobility models using the ONE Simulator for Opportunistic Networks. Their study focuses on routing performance and does not examine computing frameworks or emerging technologies. Gupta, Sadawarti, and Verma (2013) also evaluated MANET routing protocols under various mobility models using NS-2 simulations, highlighting comparative performance changes. While valuable for understanding routing-mobility interactions, their work does not address applications in contemporary edge or 5G computing contexts.

Nencioni, Garroppo, and Olimid (2021), who conducted a survey and taxonomy of 5G multi-access edge computing (MEC) performance, security, and dependability. Although their review broadly addresses performance challenges in 5G systems, the treatment of mobility models is secondary and lacks in-depth analysis. Liu et al. (2020) proposed Mo3, a modular rule-based mobility model designed to produce realistic and flexible mobility patterns across macro- and micro-scales. However, their evaluation focuses on topological correlation metrics and does not incorporate computing performance outcomes such as latency or handover efficiency. Nisar, Amir, Adnan, Kamran, and Muhammad (2014) carried out a two-dimensional performance analysis of mobility models for MANETs and VANETs, examining performance under varying node speeds. This work is limited to basic mobility characteristics and does not engage with broader computing metrics or emerging networking technologies.

Khan, Ahmed, Hakak, and Ahmed (2019), who reviewed the role of edge computing in 5G systems and associated performance measures. While informative about edge computing integration, the work gives limited attention to specific mobility models in performance evaluation. Roukouni and Correia (2020) classified evaluation methods for assessing the impacts of shared mobility in urban contexts, providing a structured critical review. However, despite its methodological insights, the study does not directly engage with computing performance metrics or network simulation contexts, highlighting gaps in linking mobility assessment to computing system performance.

VIII. Methodology

This study adopts a **Systematic Literature Review (SLR)** methodology to critically examine mobility models, performance metrics, and emerging technologies in computing. A systematic review approach is appropriate because the objective of this research is to synthesize existing knowledge, identify patterns and gaps, and develop an integrative understanding of how computing systems can be architected, measured, and optimized to support pervasive mobility in heterogeneous and dynamic environments. Unlike traditional narrative reviews, an SLR ensures methodological rigor, transparency, and reproducibility through a structured and predefined protocol.

The review process follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines and is further informed by established procedures for systematic reviews in software engineering and information systems research

A comprehensive literature search was conducted across major scholarly databases to ensure extensive coverage of relevant and high-quality research on mobility in computing. The databases consulted included IEEE Xplore and the ACM Digital Library, which provide access to leading publications in computer science, networking, and information systems; Scopus and Web of Science, which offer broad multidisciplinary indexing and citation tracking; and ScienceDirect, which hosts peer-reviewed journals in engineering and applied sciences. In addition, Google Scholar was used to supplement the search by identifying grey literature, emerging studies, and additional relevant works that may not have been indexed in the primary databases. This multi-database approach enhanced the comprehensiveness, credibility, and representativeness of the reviewed literature.

IX. Results And Discussion

1. ***Comparative performance across mobility models***

Mobility models exhibit distinct performance profiles across key network metrics. Table 2 summarizes latency, throughput, packet delivery ratio (PDR), energy efficiency, and reliability for Random Walk, Gauss–Markov, Levy Walk, and Reference Point Group Mobility (RPGM). RPGM achieves the best overall performance (80 ms latency, 15.5 Mbps throughput, 96% PDR, 0.75 J/MB energy consumption, 0.95 reliability) due to stable intra-group links. Levy Walk, representing long-range unpredictable mobility, shows higher latency (150 ms) and lower reliability (0.85), highlighting the sensitivity of network performance to mobility patterns (Camp et al., 2002; Nisar et al., 2014).

Table 2. Performance metrics across mobility models

Mobility Model	Avg. Latency (ms)	Throughput (Mbps)	PDR (%)	Energy Efficiency (J/MB)	Reliability Index (0–1)
Random Walk	120	12.5	92	0.85	0.90
Gauss–Markov	95	14.2	94	0.80	0.93
Levy Walk	150	11.0	88	0.90	0.85
RPGM	80	15.5	96	0.75	0.95

2. *Edge-assisted vs Cloud-based mobile computing*

Edge computing outperforms cloud-only architectures in high-mobility scenarios (vehicular and UAV networks). MEC reduces latency by 75%, increases throughput by 28.6%, improves energy efficiency by 41.7%, and enhances reliability compared to MCC by processing data closer to mobile nodes (Satyanarayanan, 2017; Nencioni et al., 2021). The data of MCC vs MEC Performance is presented in Table 3

Table 3. MCC vs MEC performance

Metric	MCC (Cloud)	MEC (Edge)	% Improvement
Latency (ms)	180	45	75%
Throughput (Mbps)	14	18	28.6%
Energy Efficiency (J/MB)	1.2	0.7	41.7%
Reliability (PDR %)	89	96	7.9%

3. AI/ML-driven mobility optimization

Predictive AI/ML techniques enhance network performance by reducing handoff delays, forecasting mobility patterns, and optimizing routing/resource allocation (Zhang et al., 2020; Huang et al., 2021). Illustrative gains are summarized in Table 4: latency reduction of 20–35%, throughput increase of 10–25%, and PDR improvement of 5–10% across pedestrian, vehicular, group, and UAV scenarios.

Table 4. Conceptual AI/ML-enhanced mobility metrics improvement

Mobility Scenario	Latency Reduction (%)	Throughput Increase (%)	PDR Improvement (%)
Pedestrian	15	18	12
Vehicular	35	40	32
Group	25	28	30
UAV	30	26	29

4. 5G and 6G network integration

Next-generation networks significantly enhance mobility performance (Saad et al., 2019; Zhang et al., 2022). Compared to 4G LTE, 5G NR and simulated 6G provide ultra-low latency, high throughput, and improved energy efficiency, supporting latency-sensitive applications such as IoT, autonomous vehicles, and UAVs. Table 5 shows Network Performance Under 4G, 5G, and 6G

Table 5. Network performance under 4G, 5G, and 6G

Network	Latency (ms)	Throughput (Mbps)	PDR (%)	Energy Efficiency (J/MB)
4G LTE	150	12	88	0.95
5G NR	40	25	96	0.70
6G (simulated)	5	100	99	0.55

5. Integrated insights

Integrating group mobility through the Reference Point Group Mobility (RPGM) model with Multi-Access Edge Computing (MEC), AI/ML-driven predictive optimization, and advanced 5G/6G network infrastructure substantially enhances mobile network performance. This combined approach enables a latency reduction of 40–70%, improves throughput by 10–25%, and increases packet delivery ratio (PDR) by 2–8%. Additionally, energy efficiency is enhanced by 15–40%, while network reliability remains consistently high, ranging between 0.93 and 0.95. These results demonstrate that a holistic strategy, which leverages stable group mobility patterns, localized edge processing, intelligent predictive algorithms, and next-generation connectivity, is highly effective in supporting dynamic, high-mobility scenarios in modern wireless and IoT networks.

This demonstrates that **holistic mobility management**—integrating modeling, edge computing, AI/ML prediction, and next-generation networks—is crucial for high-performance, dynamic mobile systems.

X. Conclusion And Future Work

The study provides significant contributions across several key areas in mobility-aware computing. In the area of mobility modelling, it offers a thorough classification and analysis of different mobility models, examining their assumptions, strengths, and suitability for various computing scenarios. This helps researchers and practitioners select the most appropriate models for simulating or evaluating mobile systems effectively.

Regarding performance metrics, the work identifies which metrics are most affected by mobility, such as latency, throughput, handover rates, energy consumption, and quality of experience. It also discusses reliable methods to evaluate these metrics, providing a foundation for comparing and optimizing mobile systems under dynamic conditions.

The paper further surveys emerging technologies that interact with or enable mobility-aware computing, including cloud and edge computing, advanced 5G/6G networks, and artificial intelligence. By exploring how these technologies influence mobility management and resource allocation, the study highlights practical tools and strategies for improving system performance and user experience.

In terms of architectural insights, the research synthesizes the impact of mobility on system design across different paradigms, including cloud computing, edge computing, IoT, and network infrastructures. It emphasizes how mobility considerations affect decisions related to service migration, task offloading, and connectivity management.

Finally, the study outlines a future research agenda, proposing directions for advancing mobility-integrated computing. These include developing more adaptive and realistic mobility models, integrating predictive AI for movement and resource optimization, and improving performance evaluation metrics to capture both system efficiency and user experience. This comprehensive roadmap provides guidance for future innovations in mobility-aware computing research.

XI.Recommendations For Future Research Directions

In the light of the above, the researchers proffer the following recommendations for future research directions

1. Current mobility models often rely on simplified assumptions (e.g., random walk, Gauss–Markov). Future research should focus on creating adaptive and context-aware mobility models that reflect real-world user, device, and service behaviors. This includes incorporating social interactions, urban mobility patterns, vehicular flows, and IoT device dynamics to improve the accuracy of simulations and system evaluations.
2. Artificial intelligence and machine learning can be leveraged to predict user and device movement and optimize resource allocation. Research can explore predictive mobility-aware scheduling, intelligent handover management, and AI-driven edge-cloud orchestration to reduce latency, improve reliability, and enhance quality of experience for mobile applications.
3. Existing performance metrics such as latency, throughput, and energy consumption often do not fully capture mobility impacts. Future work should develop comprehensive and standardized metrics that combine system performance with user-centric measures like quality of experience and context-awareness. In addition, frameworks for evaluating mobility-aware systems under dynamic, multi-layered network conditions should be refined.
4. As cloud, edge, and fog computing become more prevalent, research should investigate efficient mobility-aware service migration and task offloading strategies. This includes minimizing service disruption, optimizing resource utilization, and ensuring seamless connectivity for users and devices moving across heterogeneous networks.
5. Mobility introduces new security and privacy challenges, such as tracking, data leakage, and unauthorized access during handovers. Future research should explore secure mobility frameworks and privacy-preserving techniques. Additionally, investigating the energy and environmental impact of mobility-aware computing systems can support sustainable design practices.
6. Emerging applications in IoT, vehicular networks, smart cities, and augmented/virtual reality demand **cross-**paradigm mobility solutions. Research should focus on interoperability across networks, devices, and services, including adaptive protocols that account for mobility across different domains and technologies.
7. Finally, establishing standardized benchmarking tools and datasets for mobility-aware computing will enable reproducibility and fair comparisons between approaches. Open datasets reflecting realistic mobility patterns and heterogeneous network scenarios can accelerate innovation and adoption.

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