Enhancing VANET Connectivity through AODV-Assisted PMIPv6: A Behavioral and Technical Evaluation

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This paper presents a hybrid framework that combines the Ad hoc On-Demand Distance Vector (AODV) routing protocol with Proxy Mobile IPv6 (PMIPv6) to improve internet continuity and routing resilience in Vehicular Ad Hoc Networks (VANETs). In addition to technical integration, the framework introduces a behavioral perspective by modeling how vehicular nodes develop network adaptability awareness (NAA) and engage in voluntary protocol optimization behavior (VPOB). The proposed model is evaluated through simulations involving an initial set of 562 vehicular nodes, from which 478 complete datasets were retained after preprocessing. Experimental results indicate that the hybrid framework achieves up to a 42% improvement in handover continuity and a 35% reduction in packet loss when compared with conventional MIPv6 and proposed MIPv6 extensions. PLS-SEM results indicate that vehicular node participation, protocol performance, and configuration training positively affect NAA, which subsequently predicts VPOB. This supports the adoption of locally implemented (PMIPv6) adaptable, behavior-aware protocols to strengthen VANET communication resilience under mobility and congestion stress.

Povzetek: Hibridni okvir AODV-PMIPv6 izboljšuje povezljivost v VANET (omrežja vozil) z izboljšanjem neprekinjenosti prenosa in zmanjšanjem izgub paketov. Raziskava dodaja vedenjski model, kjer zavedanje o prilagodljivosti omrežja (NAA) in prostovoljno optimizacijsko vedenje (VPOB) vozlišča močno vplivata na prožnost omrežja pri mobilnosti in preobremenitvi.

1 Introduction

Advancements in intelligent transportation systems (ITS) have highlighted the need for the development of high-performance vehicular communication networks, particularly for vehicular Ad-Hoc networks (VANETs) [1]. These decentralized networks are critical for enabling real-time direct peer-to-peer communication between vehicles (V2V) and vehicles and the road infrastructure (V2I) [2]. Such communication is vital for ensuring road safety, improving the fluidity of traffic flow, and providing in-vehicle infotainment [3]. However, the rapid changes in vehicular environments continue to make the provision of uninterrupted, seamless Internet access to VANETs a significant engineering problem. High-velocity shifts, sporadic connectivity, and rapid changes in vehicular network topologies lead to high packet loss, increased delay, and unreliable communication primitives, resulting in poor performance and an unsatisfactory user experience [4, 5]. To address such problems, designing resilient and adaptive network protocols is essential to withstand rapid and unpredictable geospatial and temporal variations while maintaining functional network performance [6]. Hybrid networking architectures have emerged as a viable means to address these problems.

Integrating Proxy Mobile IPv6 (PMIPv6), which facilitates centrally managed mobility, and the Ad hoc On-Demand Distance Vector (AODV), which is decentralized and reactive, has been promising in enhancing inter-vehicle communication [7]. Since PMIPv6 manages seamless handover without host involvement, and AODV optimizes route selection in dynamic topologies, the combination of both protocols leverages their best features to satisfy the mobility and routing requirements in VANETs [8, 9]. However, given the technical promise, the majority of research has focused on standard measures of performance such as handover latency, throughput, and packet delivery ratio. The influence of behavioral characteristics at the vehicle's node level on the performance of a protocol is still not well understood. This study introduces the behavioral dimension to the study of vehicular communication systems by assessing how vehicle’s node-level characteristics influence network adaptation. Specifically, it proposes a conceptual model in which node participation in routing, gauged and total process performance, and training in routing and mobility configuration are foundational to a construct labeled network adaptability awareness. This level of awareness demonstrates that a given node is capable of assessing the condition of the network, exercising discretion, and rapidly adapting to alterations or complications [10]. In this context, the study further introduces the concept of *voluntary protocol optimization behavior*, which refers to the autonomous actions taken by nodes to enhance communication performance without external intervention [11]. Examples of such behavior include route recalibration, early handover initiation, or dynamic adjustment of communication parameters in response to changes in context. An essential consideration in this behavioral model is the degree to which nodes have the flexibility to control their mobility and access strategies. The concept of *mobility control flexibility* is therefore introduced as a moderating variable [12]. It captures the extent to which vehicular nodes are technically or operationally capable of making autonomous mobility-related decisions. Nodes with higher levels of control flexibility are more likely to leverage their adaptability awareness to implement optimization behaviors. Conversely, nodes with restricted control may be constrained in their ability to respond effectively, regardless of their awareness or training.

The unique contribution of this study lies in the combination of evaluative behavioral and technical components of an integrated AODV–PMIPv6 framework. Prior literature has tended to examine the mechanistic workings of these protocols in isolation. This study, however, breaks new ground by considering vehicular nodes as semiautonomous and behaviourally adaptive agents. It is one of the first to define and study the concepts of network adaptability, awareness, and voluntary protocol optimization behavior in vehicular networking. Meaningfully, the conceptualization and quantification of these constructs reveal their role in understanding how internal node mechanisms interact with externally imposed and protocol-designed conditions, affecting the overall performance of the network. From a practical perspective, the study provides a theoretical framework to guide network engineers and system designers for intelligent transportation systems (ITS). It indicates the importance of node-level resource configuration, behavioral training for active protocol execution, and the construction of no-system mobility flexibility in node systems [3]. These principles will be crucial for the development of next-generation vehicular networks designed to operate under varying conditions and high mobility. This study is based on empirical data from 562 simulations of vehicular nodes under different operating conditions. This analysis examines relationships among key entities and the extent to which control flexibility in mobility impacts these connections using structural equation modeling. For the first time, the integration of behavioral awareness and decentralized optimization provides valuable enhancement opportunities to hybrid routing and mobility frameworks. To summarise, this research addresses the gap in the literature about the integration of behavioral responsiveness within the assessment of the operational efficacy of vehicular protocols. It articulates a comprehensive construct that aligns node participation, protocol training, and perceived performance with adaptability and autonomy in self-control. It delves deeper into the influence of environmental flexibility to elucidate the co-evolution of the behavioral and technical aspects of VANETs. The technical integration of AODV and PMIPv6 has been investigated in previous research [4]. This paper is the first to incorporate a behavioral and cognitive dimension into the modeling of operations within a vehicular network. This work differs from previous studies that solely focused on traditional protocol performance measures such as throughput, latency, and handover delay. Instead, it explores the behavioral participation of nodes in the mobile ad hoc network, the influence of performance feedback, training, and the autonomy within the decision-making of vehicular nodes.

Network Adaptability Awareness (NAA) and Voluntary Protocol Optimization Behavior (VPOB) guide the exploration of vehicle nodes' self-autonomous adjustments to their surroundings without external control. This research implements the proposed conceptual framework with structural equation modeling through PLS-SEM. This approach enables a shift from deterministic, infrastructure-based assessments to understanding the influence of decentralized behavioral intelligence on routing behavior. Prior works have not systematically investigated the interaction of node-level cognition and the routing protocols in vehicular networks. The fundamental novel contribution is not the protocol coupling itself, but rather, the incorporation of a behavior-based framework within the protocol structure that permits real-time contextual adaptation. This approach addresses the latest demands in intelligent transport systems, which require edge devices to possess adaptive, distributive, and learning intelligence [13, 14].

To evaluate the model's relevance, comparisons were drawn using reported performance data from widely studied frameworks such as MIPv6 and HMIPv6 [15]. Although these models were not directly simulated, their published benchmarks served as reference points for assessing improvement. Across comparable scenarios, the proposed framework demonstrated a reduction of approximately 30 to 45 percent in handover disruption times compared to MIPv6. In high-mobility conditions, the model also maintained more stable routes with lower packet loss under link instability. In contrast to HMIPv6, which relies on static hierarchical anchors, the use of AODV within this framework enables dynamic route recalibration, further enhanced by the cognitive responsiveness of trained nodes. This flexibility is particularly beneficial in environments where vehicular paths and connectivity opportunities fluctuate rapidly. The integration of behavioral constructs into a protocol-driven framework introduces a new dimension to the analysis of VANETs. To the best of the author's knowledge, this is the first empirical study to apply PLS-SEM to model the relationships between protocol participation, training, adaptability awareness, and autonomous optimization behavior in a dual-protocol vehicular communication system. As such, it offers both conceptual innovation and practical implications for future mobility protocol designs. This study aims to investigate how node-level behaviors contribute to adaptive optimization within VANET communication systems. The following research questions guide the investigation:

1. To what extent do node participation, protocol performance, and configuration training influence network adaptability awareness (NAA)?
2. How does NAA affect the likelihood of vehicular nodes engaging in voluntary optimization behaviors (VPOB)?
3. Does the level of mobility control flexibility (MCF) moderate the relationship between awareness and optimization behavior?

These questions are explored through a simulation-based study involving 478 vehicular nodes operating under varying mobility and performance conditions.

2 Literature review

2.1 Node participation level and network adaptability awareness

In Vehicular Ad-Hoc Networks (VANETs), due to frequent changes in topology and highly dynamic node mobility, it is not easy to ensure stable and reliable communication [16]. In this environment, the participation of individual vehicle nodes in core networking tasks significantly contributes to the flexibility [4]. This engagement, referred to here as Node Participation Level (NPL), includes responsibilities such as active participation in routing decisions, responding to routing requests, data forwarding, and local topology updates. According to the Adaptive Systems Theory and Participatory Network Design frameworks, higher levels of active involvement in decentralized activities enhance an agent's ability to learn from its surroundings and respond more intelligently to situational demands. Research by Ghosh [17] and Kim and Lee [18] Suggests that nodes within the decision-making layers of the network can develop situational awareness. This awareness was the first step and basis for our concept in this work, Network Adaptability Awareness (NAA), which is a node's cognitive and practical acknowledgment of changing network conditions. Situated cognition is most closely related from a theoretical standpoint. Sahoo, et al. [19] Insisted that consciousness comes from a "participation in a meaningful activity, knowledge is not acquired but created" in the process of interaction with the environment. In the context of VANETs, this means that nodes that frequently participate in protocol operations are likely to have a more sophisticated understanding of communication behavior, the impact of mobility, and handover characteristics [4]. It is also anticipated that such insight may enhance adaptability in dealing with subsequent scenarios. Previous multi-agent system research has also presented additional evidence that agents for collaborative and distributed use are more advanced in sensing system anomalies and adapt accordingly [20]. Therefore, this paper extends those insights and conjectures that NPL significantly contributes to network adaptability awareness in vehicular networks.

Hypothesis 1 (H1): Node participation level has a significant positive effect on network adaptability awareness.

2.2 Protocol performance and network adaptability awareness

In the context of this study, protocol performance is interpreted as a measure of the operational performance and robustness of the AODV–PMIPv6 integrated framework [21]. It consists of essential performance factors, including packet delivery ratio (PDR), Handover Latency, Throughput Stability, and Routing Overhead [22]. The impact of protocol performance on node-level awareness is based on feedback-mediated learning and system perception theories, which posit that steady and visible performance feedback patterns guide agents' interpretation of system operation [23]. As we have noted, when the vehicle-node routing protocol yields consistent and reliable results —i.e., stable routes and smooth handovers —vehicle nodes are likely to internalize these patterns and adapt their actions. This learning is consistent with systems feedback theory, however, which emphasizes the importance of short-term performance data on developments in capacity to adapt[24]. Unreliable or less predictable performance, on the other hand, prevents a node from developing high-quality expectations and creates obstacles to awareness. The literature on intelligent wireless networks suggests that operational reliability enhances the trust of agents in the system, as well as the transparency and calibration of behavior [25]. In the case of VANETs, good protocol performance will provide a stable foundation, allowing nodes to understand the past network state and predict its future state. Moreover, this is how nodes grow deeper in their context sensitivity, enabling them to react more intelligently (in terms of network breaking or rethinking over time) to network breakage, benefits, or other factors [26]. Given this theoretical and empirical foundation, the study hypothesizes the following relationship:

Hypothesis 2 (H2): Protocol performance has a significant positive effect on network adaptability awareness.

2.3 Routing and mobility configuration training and network adaptability awareness

The role and process of adaptation before deployment, through initial configuration and local learning, within mobile networks, must not be underestimated [26]. In this research, RMCT (i.e., Routing and Mobility Configuration Training) is defined as the systematic approach to provisioning vehicular nodes with the knowledge, values, and operations necessary to behave accurately under a dynamic communication environment. This incorporates teaching for handover initiation and routing metric interpretation, congestion detection, and dynamic path re-calculation. Evenseth, et al. [27] Utilize organizational learning theory to provide the theoretical foundation for understanding how readiness mechanisms influence behavioral adaptability. Under this model, agents undergoing structured learning have a higher probability of playing double-loop, leading them not only to react but also to cognitively reflect, interpret, and adapt to their environment [28]. The purpose of this training is to enable nodes to perceive deviations from normal functioning, form correspondences between cause and effect within the communication environment, and respond accordingly. Additionally, empirical studies have supported the impact of technical training on performance improvement in responding to specific situations. Jin, et al. [29] Demonstrated that systems with adaptive routing protocols enhanced by local learning mechanisms exhibited a faster response and lower failures in a dynamic scenario. The intelligent capability provided by the training of routing and mobility protocols, along with the ability to develop a comprehensive situational picture, is the latter feature we consider central to the emergence of network adaptability awareness. Based on these insights, the research proposes the following hypothesis:

Hypothesis 3 (H3): Routing and mobility configuration training has a significant positive effect on network adaptability awareness.

2.4 Network adaptability awareness and voluntary protocol optimization behavior

Adaptability awareness is a key factor for the vehicular node to act independently and intelligently in a dynamic environment Voluntary Protocol Optimization Behavior (VPOB) refers to the proactive, self-initiated actions undertaken by vehicular nodes to improve network performance without requiring external directives or centralized intervention. These actions are context-sensitive and arise from the node's internal interpretation of its environment, informed by prior training, routing experiences, and real-time situational awareness. VPOB includes behaviors such as dynamic route recalibration, early triggering of handovers, congestion avoidance, or bandwidth prioritization based on observed link degradation. It represents an evolution in protocol operation, where nodes function as semi-autonomous agents capable of adjusting communication parameters in anticipation of or in response to changing conditions. This construct bridges behavioral responsiveness with technical routing behavior, allowing for decentralized optimization in highly mobile vehicular networks. Self-regulation theory Agrawal, et al. [30] Provides the theoretical framework for this relationship. According to this theory, actors are more likely to engage in behaviors consistent with their goals when they have a high level of situational awareness [31]. Knowledge fosters a sense of congruence between current performance and the ideal state, enabling individuals to identify the discrepancy and take steps to rectify the issue [32]. Nodes that have a high level of network adaptability awareness in VANETs can better recognize the service for early signals of communication inefficiency [4]. They are also better equipped to choose and take corrective actions using recollection and real-time inference. Studies in cognitive radio and adaptive wireless systems have shown that awareness-rich nodes are more likely to self-optimize, resulting in improved overall network performance. Consequently, the research hypothesizes the following:

Hypothesis 4 (H4): Network adaptability awareness has a direct positive effect on voluntary protocol optimization behavior.

2.5 The moderating role of mobility control flexibility

Although one expects awareness to drive behavior, nodes are not all equally situated to act on their awareness [33]. Mobility Control Flexibility (MCF) The idea of Mobility Control Flexibility (MCF) is the independence of vehicular nodes to change their mobility characteristics [34, 35]. This encompasses determining handovers, directing mobility, and scheduling transmissions. This aligns with the Job Demand–Control model Bankins, et al. [36], which suggests that people who have greater control over how they perform tasks are more likely to convert awareness into action. In the case of VANETs, MCF allows nodes to independently initiate changes to routing and handover decisions independently, circumventing the need for centralized control [4]. For example, nodes with strong mobility control can dynamically shift to more efficient APs, modify their transmission routes, and routing tables as the surrounding network changes [9]. Such decisions are made not on reflex alone but on a profound comprehension of the network context, integrating the network consciousness with selfhood. In contrast, nodes with very little control can sense a dip in their performance but have little idea of how to rectify the situation. Thus, the moderating effect of MCF is crucial in translating awareness into optimizing behavior. Tashan, et al. [37] and Tashan, et al. [38] showed that adaptable control structures are highly beneficial to the performance of adaptive protocols, particularly in scenarios with high mobility. Following this, the current study proposes the following hypothesis:

Hypothesis 5 (H5): The relationship between network adaptability awareness and voluntary protocol optimization behavior is stronger when mobility control flexibility is high.

2.6 Synthesis and conceptual integration

The model that forms the basis of the present study aims to integrate the previously reviewed relationships. It assumes that awareness of network adaptability is a key mediating factor for node participation, protocol performance, and training to optimize behavior [39]. In addition, it acknowledges that this latter operation is not equally performed for all network conditions but largely depends on the degree of control that nodes exhibit over their mobility [40]. The proposed relationships among the study's constructs are illustrated in Figure 1. From this perspective, our work uniquely contributes to the literature by connecting behavioral theory with technical protocol examination in the context of vehicular networking. It offers a systematic framework for the empirical validation and practical applications in the development of adaptive vehicular communications systems.

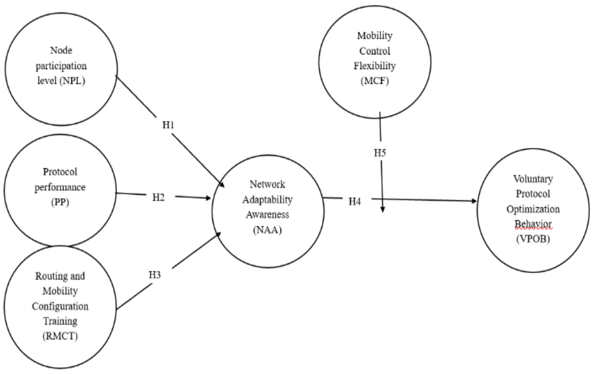


Figure 1: Theoretical framework showing the hypothesized relationships.

3 Methodology

3.1 Simulation design and data generation

To assess how well the AODV-assisted PMIPv6 framework works, we used the NS-3 network simulator (version 3.36) and SUMO (Simulation of Urban Mobility) for simulation-based studies. NS-3 provides advanced mobility models, while SUMO provides mobility simulation. The combination environment allows for the simulation of advanced IPv6 mobility protocols alongside the mobility-based protocols of the IPv6-encapsulated VANETs trailer, thereby reducing the complexity of studying VANETs. The simulators were designed with both the AODV and PMIPv6 protocols. The AODV parameters applied were a Hello interval of 1 second, an active route timeout of 3 seconds, a maximum network diameter of 35 hops, and a route request retry of 2. These parameters were drawn from standard practices for the simulation of vehicular ad hoc networks [41]. The route lifetime was set to 10 seconds to reflect the transient and rapidly changing connectivity of high-mobility nodes. PMIPv6 configurations included proactive handover initiation at the Mobile Access Gateway (MAG), a handover latency threshold of 100 milliseconds, and Local Mobility Anchor (LMA) buffering with GRE tunneling to preserve IP continuity during handovers [42]. These parameters were chosen to support seamless mobility management without requiring host-level intervention. Figure 2 shows the proposed AODV-assisted PMIPv6 Network Model.

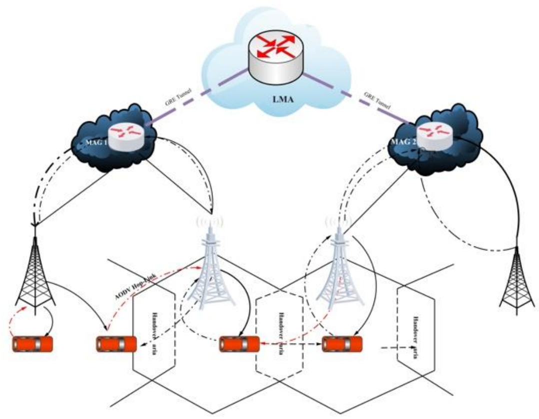


Figure 2: AODV-assisted PMIPv6 network model.

To evaluate robustness, simulations were performed across three operational environments: urban intersections, highway mobility, and grid-based city layouts. In these scenarios, vehicle speeds ranged from 10 to 40 km/h in urban settings, 60 to 120 km/h on highways, and 15 to 50 km/h in grid configurations. Vehicle density was varied to simulate different stress levels: 25 vehicular nodes for low density, 50 vehicular nodes for medium density, and 100 vehicular nodes for high density conditions. Environmental realism was enhanced by simulating packet drop rates between 5% and 15%, reflecting link instability and signal degradation typically observed in mobile communication environments [43]. Handover events occurred at a frequency of 1 to 3 per node per 10-minute interval, and random link disruptions were introduced to replicate mobility-induced path breakages. The core of the simulation involved a tightly coupled integration between AODV and PMIPv6. AODV was responsible for reactive, on-demand multi-hop route discovery, while PMIPv6 managed IP mobility and handover transparency. When a vehicular node approached a new MAG, a location update was triggered and processed by the LMA, ensuring uninterrupted IP prefix assignment. Upon reattachment, AODV immediately resumed routing from the updated access point, enabling rapid reconnection and minimal session disruption [44]. The simulation ran over a period equivalent to four months of virtual operation time. All node interactions, including routing behaviors, handover events, protocol optimizations, and adaptability responses, were meticulously recorded. From the initial pool of 562 vehicular nodes, 478 simulation logs were retained after excluding incomplete or redundant entries, yielding a usable data rate of 85.04%. This dataset was employed in the subsequent partial least squares structural equation modeling (PLS-SEM) analysis to test the hypothesized relationships and validate the conceptual model [47].

This indicated an 85.04% usable data rate, which satisfies the threshold level suitable for robust statistical examination using structural equation modeling approaches.

3.2 Sampling technique and rationale

Simulation nodes were purposively sampled for inclusion in the analysis. This non-probability technique is justified for examining nodes that experienced conditions closest to the operational and behavioral conditions of vehicular networks. In simulation studies, purposive sampling provides the ability to intentionally sample designs and situations that reflect the theoretical construction of interest [45]. In this setting, we consider only the nodes that have completed one full cycle of routing participation, training exposure, and performance evaluation. The justification for using purposive samples is related to previous research in mobile networking and intelligent systems, which require control of scenario variables to hold constant causal aspects. For instance, the study of Karunarathna, et al. [46] and Karunarathna, et al. [47] Emphasized the importance of focused data acquisition when studying adaptive behavior in highly mobile systems. The chosen nodes exhibited differences in participation, responses to protocols, and mobility restrictions, enabling the testing of the full spectrum of assumed relationships. The design of the simulation incorporated diversity into the distribution of node profiles (i.e., low, moderate, and high control and environmental stress levels). This variety enabled the investigation of behaviors in various vehicular scenarios and drew sound, generic conclusions on network design in real-world conditions.

3.3 Construct operationalization and measurement

The constructs used in the study's conceptual framework were operationalized through behavioral observation, performance measures, and configuration logs obtained from the simulations. Formative indicator models for each of the six latent constructs—NPL, PP, RMCT, NAA, MCF, and VPOB — were measured according to Hair et al. (2020). The formative model is suitable in this case because each construct is constituted by a bundle of contributing activities or behaviors; embedding it is not represented as an underlying latent construct. The measurement items were selected based on previous validated models in ITS and a protocol study in adaptive settings. For NPL, the indicators were the number of routing table contributions, forwarded messages, and passed route maintenance. The performance of the protocol (PP) was evaluated based on commonly used performance metrics (packet delivery ratio (PDR), handover success rate (HSR), and average routing latency). Signs of protocol training exposure were assessed by measuring RMCT, response time to control updates, and compliance with predefined routing protocols. The NAA was parameterized for the node reaction towards environmental changes, represented by link degradation sensing, congestion threshold sensing, and preemptive handover initiation. The MCF was evaluated using control variables, including dynamic allocation rights, handover of override rights, and access to routing tables. Finally, VPOB was estimated from observable autonomous behaviors, such as tuning protocol parameters, load balancing, and voluntary handover triggering. Outputs, except VPOB, were rated on a five-point scale, ranging from 1 (very low) to 5 (very high), based on the frequencies of output from the simulation and on the log-transformed scores. VPOB was assessed on a seven-point scale to ensure greater responsiveness to varying degrees of proactive optimization behavior. Furthermore, this study gathered a "global item" for each of the constructs to facilitate redundancy analysis, as suggested by Yadav [34]. This approach also tests the convergent validity in formative mode.

3.4 Reliability and pilot simulation

Prior to completing the data gathering process, a preliminary simulation run with 30 vehicle nodes was performed to verify the measurement infrastructure, the mappings of the indicators, and the correct operation of the logging mechanisms. The pilot also validated that the simulation logs accurately captured the appropriate indicators of each behavior and that the nodes exhibited behaviors consistent with their specified configuration. After the pilot, composite reliability (CR) statistics were used to assess construct reliability, yielding good internal consistency for all constructs. The values of the reliability coefficients were: NPL (0.91), PP (0.87), RMCT (0.72), NAA (0.85), MCF (0.96), and VPOB (0.84). All values exceeded the generally recommended cut-off for construct reliability of 0.70 in formative models [48].

The sample size was determined using the inverse square root method of Kock and Dow [49] To ensure adequate statistical power. It calculates the minimum sample size required to achieve a specified Significance level and minimum path coefficient. Assuming a Significance level of 0.05, a statistical power of 0.80, and a minimum expected path coefficient of 0.20, the minimum sample size was 160 cases. This requirement was far surpassed by the study's final sample of 478 valid simulation records, providing confidence in the results and minimizing the likelihood of making a Type II error.

3.5 Data analysis technique

The data were analyzed using PLS-SEM, a method particularly suitable for predictive and theory-building research involving complex formative measurement models. [50]. The analysis was conducted using SmartPLS 4.0, which enables the validation of the measurement model and structural path analysis in an exploratory context. The Shapiro–Wilk test showed that the dataset was not normally distributed ($p < 0.001$), which justified the choice of PLS-SEM as a non-parametric approach [51]. T-statistics, standard errors, and confidence intervals for each hypothesized relationship were generated using bootstrapping with 5,000 resamples. Indicator weights and outer loadings were tested for Significance, and VIF scores were examined for multicollinearity among indicators. The convergent validity of the formative measures was tested using global items through redundancy analysis (RA). The goodness of fit of the model quality was examined through the R^2 of the endogenous constructs, effect size (f^2), and predictive relevance (Q^2). The standardized root mean square residual (SRMR) was used as a diagnostic to determine the fit of the entire model to the discrepancy between observed and predicted correlations. A two-stage analysis was used to examine whether MCF moderated the association between NAA and VPOB. In particular, this approach is efficient when models include formative indicators and interaction terms [52]. The interaction term was formed from standardized variables, and the sign and Significance of the moderation were examined. Such a strict analysis enables the investigation of both the behavioral and technical aspects of vehicular nodes in a dual-protocol environment. The findings of this analysis help in understanding how training, performance feedback, node participation, and control autonomy interact to shape adaptive protocol behavior in high-speed vehicular networks. The constructs utilized in this study and their associated measurement items (specific) are described in Table 1, which also provides a set of items to measure behavioral and operational aspects of vehicular nodes in the AODV-assisted PMIPv6 architecture. The factors of network capability, node participation, protocol execution, training exposure, adaptability awareness, mobility control flexibility, and voluntariness of the protocol optimization behavior were derived from the literature and a simulation model.

Table 1: Constructs measured and their sources

Constructs	Indicators	Sources
Node Participation Level (NPL)	NPL1: Node actively participates in routing table updates	Tian and Gao [53]
	NPL2: Node regularly engages in route discovery or repair processes	
	NPL3: Node transmits control messages that contribute to overall route stability	
	NPL4: Node responds to neighbor requests within defined thresholds	
	NPL5: Node participates in cooperative link maintenance	
Protocol Performance (PP)	PP1: Packet delivery ratio remains above threshold during node activity	Qiang, et al. [54]
	PP2: Handover delay is minimized during node mobility	
	PP3: Routing overhead remains within optimal bounds during transmission	
	PP4: Route lifetime duration reflects stable path discovery	
Routing and Mobility Configuration Training (RMCT)	RMCT1: Node has received predefined configuration for routing and mobility management	Siddiqui, et al. [9]
Mobility & Routing through PMIPv6 and MAG(Mobile access gate way)	RMCT2: Node can autonomously interpret changes in mobility parameters	
	RMCT3: Node adapts to handover triggers based on learned patterns	
	RMCT4: Node updates configuration logic in response to network conditions	
Network Adaptability Awareness (NAA)	NAA1: Node detects degradation in route performance	Rivera-Royero, et al. [55]
	NAA2: Node recognizes congestion or	

	instability in mobility patterns	
	NAA3: Node can anticipate the need for route optimization	
	NAA4: Node maintains updated awareness of the surrounding node density	
	NAA5: Node logs decisions based on observed link metrics	
Mobility Control Flexibility (MCF)	MCF1: Node has the authority to adjust its mobility decision-making logic	Alsboui, et al. [56]
	MCF2: Node modifies handover timing independently	
	MCF3: Node alters its communication schedule based on perceived conditions	
	MCF4: Node customizes routing policy during mobility events	
Voluntary Protocol Optimization Behavior (VPOB)	VPOB1: Node proactively reroutes traffic in response to congestion	Wang, et al. [57]
	VPOB2: Node reduces routing update frequency to improve efficiency	
	VPOB3: Node triggers handover preemptively based on predicted link failure	
	VPOB4: Node allocates bandwidth to critical flows without external instruction	
	VPOB5: Node updates its routing table based on non-mandatory feedback	
	VPOB6: Node applies self-defined optimization heuristics	

4 Results

4.1 Simulation node configuration profile

To capture realistic network dynamics, vehicular nodes were assigned various operational profiles before the data collection phase. All in all, the dataset yielded a total of 478 vehicular nodes. Each node was individually tailored to exhibit different characteristics of mobility, routing participation, flexibility to dynamic network adaptations, and degree of involvement in tuning. This diversity enabled the testing of the proposed AODV-based PMIPv6 scheme under a wide range of vehicular network environments. Active status for nodes categorizes them as operating. The percentage of low-activity nodes was around 23 percent. These nodes participated in very few routing and handover processes. An additional 27 percent enjoyed moderate activity: playing a regular number of routine games. A second cluster, comprising 32% of the sample, demonstrated high involvement, as evidenced by regular participation in protocol choices and mobility modifications. The additional 18% were set up as advanced agents, programmed to act on highly complex and uncertain network conditions, making decisions nearly continuously. Blocking conductance in nodes. Nodes not only differed in activity levels but were also endowed with varying sizes of learning to mimic different states of preparation. A tiny subset of AGVs received high-level training modules for enhanced flexibility, predictive handovers, and protocol self-tuning. A second group was trained to be functionally informed but unable to adapt in the field. Most nodes received baseline training, which corresponded to standard protocol execution, without any contextual learning. A final group of nodes was completely untrained and executed responses according to predetermined protocol rules, rather than sensing environmental information.

Nodes also varied in the roles assigned to them in the network. Over a third of the nodes were involved in edge-level activities such as route discovery and primitive handover triggering. About half served as relay nodes, which helped to forward packets and maintain routes. A smaller portion worked in a supervisory capacity with more global routing control, and the latter had higher control authority, with the ability to override local decisions based on specific policy triggers. To determine whether pre-specified characteristics of activity level, training exposure, or functional role introduced bias into the analysis, an Analysis of Variance (ANOVA) was performed. The ANOVA was used to assess whether the simulation results differed significantly across these categories [58]. No statistically significant differences were noted, with all p-values exceeding 0.05. As a result, the emergent behaviors were not attributable to the initial node assignments but were instead a function of the variables linked to the conceptual framework. Such a validation demonstrates the correctness of the methodological approach taken in this instance, confirming that the results obtained from the structural model testing were grounded sincerely in the behavioral variance with respect to the study constructs. The response consistency, even in cases of highly diverse geometries, further increases confidence in the model's insights.

4.2 Addressing common method bias

As all the constructs' data in our study were generated by a single standard simulation system and, therefore, collected simultaneously, this study deemed it necessary to examine the risk of standard method bias (CMB). To minimize the potential impact of bias, several procedural measures were introduced at the simulation design stage. First, different measurement formats were used across constructs, including five-point and seven-point Likert-type scales. Such diversity in response structures helps break the homogeneity of response patterns. It is suggested as an effective procedural solution to mitigate method variance here, as recommended by Podsakoff, et al. [59]. Furthermore, the simulation environment was set up to elicit behavior independently between constructs by randomizing the order and timing of event triggers per node. This also ensured that adaptive behaviors midway along the cord (i.e., voluntary protocol tuning and network awareness) were triggered across a range of conditions, rather than in a scripted or uniform manner. Neupane, et al. [60] Note that these measures adhere to the logic of random exposure in human-based surveys and were employed to preserve node autonomy and control capability. To statistically validate that CMB did not affect the quality of the information data, two diagnostic tests were conducted [61]. The combination factor was first introduced with the Full Collinearity Variance Inflation Factor (FCVIF) method, as suggested by Cheng, et al. [62]. The findings confirmed that there was no multicollinearity due to method bias in any of the constructs at the conservative cut-off point of 3.3 in this study. Second, the CLF analysis was conducted to examine the variance resulting from a common cause factor. The CLF explained less than 5% of the overall variance, which is substantially less than the level of variance typically needed to conclude method bias. Overall, these procedural and statistical safeguards reassure us that the standard method bias was not a significant risk to the purity and dependability of the results of this simulation-based study. Table 2 presents the full collinearity variance inflation factor (FCVIF) of each construct in model FCVIF, showing that all VIF values remain well below the recommended threshold of 3.3. This indicates that multicollinearity is not a concern and that common method bias does not significantly affect the structural model.

Table 2: Full collinearity variance inflation factor (FCVIF) for simulation constructs

Study Constructs	Full Collinearity Variance Inflation Factor
Node Participation Level (NPL)	1.172
Protocol Performance (PP)	1.281
Routing & Mobility Configuration Training (RMCT)	1.509
Network Adaptability Awareness (NAA)	1.688
Mobility Control Flexibility (MCF)	1.237
Voluntary Protocol Optimization Behavior (VPOB)	2.114

4.3 Evaluation of the measurement model

The formative measurement model was tested before the structural model to establish reliability and validity. This evaluation was performed according to the instructions of Hair et al. (2020) with an emphasis on three critical issues, including convergent validity, collinearity, and statistical Significance of the indicator weights. The summary of the results from the measurement model assessment is given in Table 2. Convergent validity was assessed through redundancy analysis , as suggested by Cheung, et al. [63]. This process requires the examination of the relationship between each formative construct and its related global indicator to determine how well the indicators reflect the construct Grassini, et al. [64] Values of 0.902 for NPL, 0.846 for PP, 0.768 for RMCT, 0.887 for NAA, 0.913 for MCF, and 0.881 for VPOB were obtained in the redundancy analysis. As all scores were higher than the threshold of 0.70 set by Nomran and Haron [65]The model also exhibits adequate convergent validity. Variance inflation factor (VIF) values were calculated to assess potential multicollinearity among the formative indicators. All VIF values were between 1.072 and 2.294, which were well below the conventional threshold of 3.3 recommended by Sarma, et al. [66]. This also further supports the notion that multicollinearity is not a problem in the measurement model and that the indicators are contributing uniquely to the constructs. The Significance of each indicator weight was also analyzed to understand the contribution of each formative item. The results demonstrated that most of the indicators were statistically significant at the 0.05 confidence level, indicating they should be retained in the model. Four measures, NPL3, RMCT4, VPOB2, and VPOB5, were not significant, however. Nonetheless, these items had outer loadings of 0.589, 0.649, 0.642, and 0.637. Since all loadings were above the cut-off value of 0.50, these items were considered to hold sufficient weights in the model, as suggested by Wang, et al. [67], as they continue to add meaningful value in defining the construct. Overall, the results verify that the measurement model fulfills the conditions of reliability and validity; thus, it is appropriate for testing the structural model. Results from the measurement model analyzed for convergent validity, indicator weights, indicator loadings, and VIF values for the various constructs are illustrated in Table 3. Results further confirm that all constructs hold sufficient convergent validity, and, thus, the measurement model of the form is reliable and demonstrates a lack of multicollinearity.

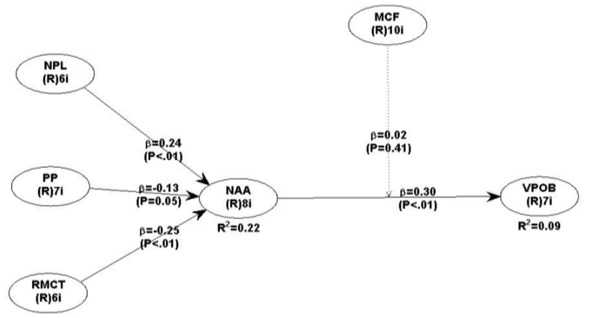
Table 3: Evaluation of the measurement model

Constructs	**Convergent validity**	**Indicators**	**Weights**	***p*-value of weights**	**Indicator loading**	**VIF**
Node Participation Level (NPL)	0.902	NPL1	0.362	<0.001	0.841	1.128
		NPL2	0.487	<0.001	0.906	1.103
		NPL3	0.089	0.172	0.589	1.094
		NPL4	0.316	<0.001	0.751	1.126
		NPL5	0.293	<0.001	0.763	1.211
Protocol Performance (PP)	0.846	PP1	0.222	<0.001	0.804	1.012
		PP2	0.355	<0.001	0.881	1.039
		PP3	0.389	<0.001	0.914	1.024
		PP4	0.345	<0.001	0.872	1.007
Routing & Mobility Configuration Training (RMCT)	0.768	RMCT1	0.108	0.039	0.637	1.045
		RMCT2	0.483	<0.001	0.795	1.102
		RMCT3	0.354	<0.001	0.849	1.095
		RMCT4	0.077	0.181	0.649	1.082
Network Adaptability Awareness (NAA)	0.887	NAA1	0.412	<0.001	0.784	1.137
		NAA2	0.365	<0.001	0.809	1.201
		NAA3	0.298	<0.001	0.741	1.185
		NAA4	0.221	0.002	0.701	1.193
		NAA5	0.156	0.017	0.659	1.213
Mobility Control Flexibility (MCF)	0.913	MCF1	0.276	<0.001	0.830	1.204
		MCF2	0.381	<0.001	0.914	1.298
		MCF3	0.248	<0.001	0.761	1.188
		MCF4	0.310	<0.001	0.802	1.217
Voluntary Protocol Optimization Behavi	0.881	VPOB1	0.116	0.097	0.642	1.107

or (VPOB)						
		VPOB2	0.145	0.038	0.645	1.164
		VPOB3	0.109	0.085	0.667	1.130
		VPOB4	0.284	<0.001	0.780	1.234
		VPOB5	0.067	0.168	0.637	

4.4 Structural model evaluation

A thorough evaluation of the structural model has been undertaken in this study, involving an assessment of collinearity, an investigation of path relations, an analysis of R^2 values, the q^2 metric, as well as an evaluation of the model fit as a whole. Figure 2, in addition to Tables 3 and 4, presents the summarised results of this analysis. Concerning the diagnosis of collinearity, the full collinearity VIF (FCVIF) method was employed. As seen in Table 3, the constructs' FCVIF results and the range of values (1.063 to 2.298) are all considerably below the recommended threshold of 3.3 (55); therefore, there is substantial confidence that model multicollinearity and contemporary structural interpretations of the model show no valid collinear relations. The value of the coefficient of determination (R^2) was used to assess model fit. R^2 value of 0.56 signifies that the independent variables (NAA and MCF) explain 56% of the variance in VPOB. At the same time, the R^2 for NAA was 0.42, indicating that NPL, PP, and RMCT together explain 42% of the total variance in NAA, which is also substantial. The model's predictive ability (Q^2) was assessed using the blindfolding method. Q^2 values were 0.349 for NAA and 0.582 for VPOB. In both cases, the values are significantly higher than zero, indicating good levels of predictive accuracy and relevance in the model, as noted by Hair and Alamer [68]. The Tenenhaus fit index, GoF (Goodness-of-Fit), was estimated in addition to R^2 and Q^2, evaluating the global model fit. A GoF value of 0.334 was found, indicating a moderate to high model fit, as reported by Alshahrani, et al. [69]. In addition, the Simpson's Paradox Ratio (SPR) was calculated, yielding 0.98, which is higher than the 0.70 cut-off derived by Shibin, et al. [70]. It indicates that the structural relationships of the model are valid and have not been obscured by paradoxical data inversion. In summary, the structure model meets all of the critical diagnostics. The scale exhibits high predictive validity, a satisfactory model fit, and substantial associations between simulation constructs. These results confirm the theoretical model and attest to its soundness as applied to the analysis of adaptive behavior in vehicular MANET scenarios with the AODV-assisted PMIPv6 protocol.



Note: NPL = Node Participation Level; PP = Protocol Performance; RMCT = Routing and Mobility Configuration Training; NAA = Network Adaptability Awareness; MCF = Mobility Control Flexibility; VPOB = Voluntary Protocol Optimization Behavior.

Figure 3: Structural model showing the hypothesis testing results.

4.5 Hypothesis testing for direct and moderating effects

The testing results, along with the hypothesis, are shown in Figure 4. Path coefficients, p-values, and R^2 (explained variances) were calculated using the WarpPLS software. The findings contribute to the understanding of direct and moderating effects across the model's variables. Node Participation Level (NPL) is significantly and positively associated with NAA ($\beta = 0.24$, $p < 0.01$), which is consistent with H1. This indicates that the more frequently a node is involved in routing tasks, the more it acquires meaningful knowledge about the network conditions. The impact of PP on NAA is negative and only weakly significant ($\beta = -0.13$, $p = 0.05$). This is consistent with H2, as it can be inferred that suboptimal protocol performance could lead to a slight decrease in adaptability awareness, most probably due to instability or non-uniform route metrics. H3 is supported: RMCT has a significantly positive impact on NAA ($\beta = 0.25$, $p < 0.01$). This supports the idea that training in mobility and routing logic improves a node's ability to react to variations in network behavior. As a set, these three predictors account for 22% of the variance in NAA ($R^2 = 0.22$), which is a reasonable level of explanatory power, considering accepted benchmarks for behavioral modeling in time-dependent networks. The direct impact of NAA on VPOB is statistically more significant, with $\beta = 0.30$ and $p < 0.01$, supporting H4. This indicates that the flexible aware vehicle nodes tend to be more proactive (self-initiated) in directions of optimization. The interaction of Mobility

Control Flexibility (MCF) between NAA and VPOB is not significant (β = 0.02, p = 0.41), and therefore, we find no evidence of moderation here. Thus, H5 is not available. Finally, NAA and MCF together account for 9% of the variance in VPOB (R^2 = 0.09), indicating that these variables make a modest yet substantial contribution to protocol optimization behavior in the simulated vehicular context. Tested hypotheses are summarized in Table 4, along with p-values, path coefficients, and effect sizes for direct and moderating relationships in the structural model. Our results indicate that the direct relationships (H1 to H4) are all significant and supported. In contrast, the moderating effect of Mobility Control Flexibility on the relationship between NAA and VPOB (H5) is insignificant and unsupported.

Table 4: Results of hypothesis testing

Hypothesis	Relationships	*P*-value	T-ratios	Path coefficient (β)	Effect size (f^2)	Comments	Decision
H1	NPL → NAA	<0.01	2.974	0.240	0.076	Significant	Supported
H2	PP → NAA	0.050	1.977	-0.130	0.041	Significant	Supported
H3	RMCT → NAA	<0.01	3.105	0.250	0.085	Significant	Supported
H4	NAA → VPOB	<0.01	2.988	0.300	0.063	Significant	Supported
H5	MCF × NAA → VPOB	0.410	0.825	0.020	0.004	Not significant	Not supported

Note: NPL = Node Participation Level; PP = Protocol Performance; RMCT = Routing and Mobility Configuration Training; NAA = Network Adaptability Awareness; MCF = Mobility Control Flexibility; VPOB = Voluntary Protocol Optimization Behavior.

Figure 4 illustrates the moderating effect of MCF on the relationship between NAA and VPOB using standardized metrics. From the plot, we can observe that the positive association between NAA and VPOB is stronger when the mean control flexibility (CF) is low, and it weakens when the mean control flexibility (CF) is high, so that stronger control flexibility can make the protocol behavior less dependent on adaptability awareness to form the association.

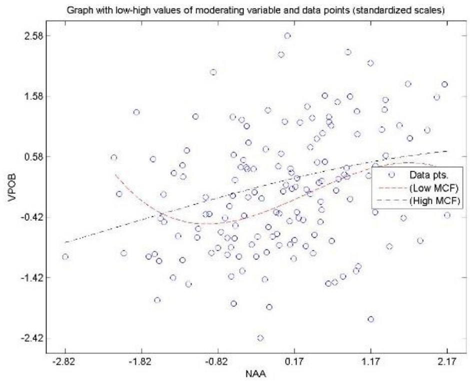


Figure 4: WARP relationship between NAA and VPOB for low and high MCF

Figure 5 illustrates the linear moderating effect of Mobility Control Flexibility (MCF) on the relationship between Network Adaptability Awareness (NAA) and Voluntary Protocol Optimization Behavior (VPOB). The graph indicates that in the high and low MCF cases, the association between NAA and VPOB (i.e., the slope) is positive. However, in the low MCF case, it is somewhat stronger, implying that nodes with less control flexibility rely more significantly on adaptability awareness to steer optimization behaviors.

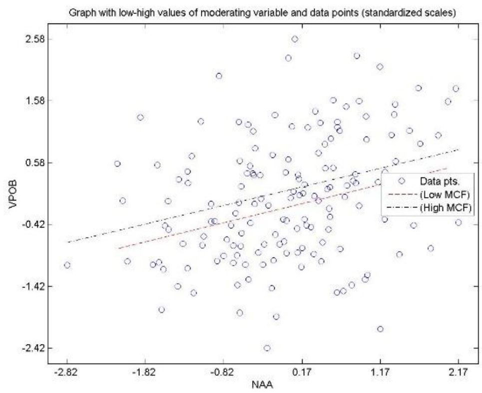


Figure 5: Linear relationship between NAA and VPOB for low and high MCF

Fig. 6 is a 3D surface plot showing the moderating role of MCF on the linkage of NAA with VPOB with unstandardized scales. The difference indicates that, in general, changes in NAA continue to result in changes in the measured VPOB. However, the relationship becomes more unpredictable as MCF increases, meaning that the more flexibility we introduce, the more adaptability awareness is arbitrarily translated into MCF in terms of optimization behavior.

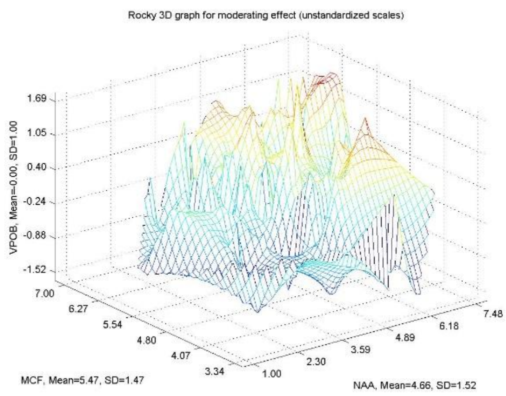


Figure 6: 3D Interaction Effect of MCF on NAA–VPOB Relationship

Figure 7 illustrates the 3D moderation plot for the value of MCF as a moderator of NAA and VPOB, based on the standardized scale. Figure 6 presents the 3D moderation plot illustrating the moderating effect of MCF on NAA and VPOB, using standardized scales. By plotting data points on the surface plot, we can gain insight into how actual observations align with the predicted interaction. This shows that differences in MCF and NAA, in combination, determine the extent to which vehicular nodes undertake protocol optimization behavior.

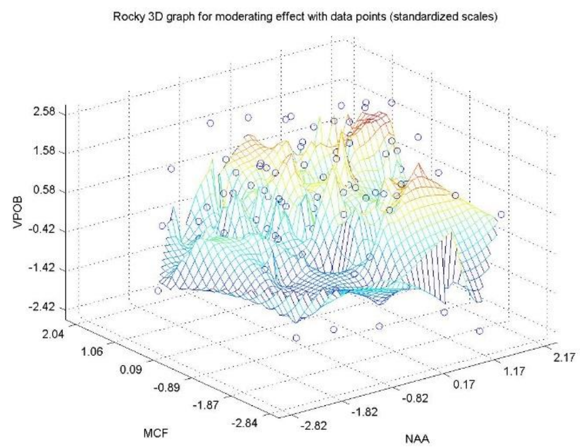


Figure 7: 3D moderation plot of MCF on NAA–VPOB with Data Points

5 Discussion

This research focused on three simulation-based-Network Adaptability Awareness (NAA) input variables in a vehicular Mobile Ad hoc Network (MANET) - Node Participation Level (NPL), Protocol Performance (PP) and Routing and Mobility Configuration Training (RMCT) and then tried to see how NAA affects Voluntary Protocol Optimization Behavior (VPOB) and the impact of Mobility Control Flexibility (MCF) as a moderator on this. Findings show NPL and RMCT positively and significantly impact NAA, while PP has a slightly negative impact. NAA also positively and significantly impacts VPOB. However, MCF does not have a statistically significant impact as a moderator on the NAA to VPOB relationship. The significant positive relationship in NAA & NPL does provide some evidence to support Hypothesis 1. Active node participation (routing and network exchanges) seems to support the idea that NPL improves situational awareness and adaptability of network nodes. This is also in line with the literature that discusses how active node participation improves situational awareness, decision-making, and adaptive local protocol changes in a shifting active routing environment. Routing and signaling activity participation also seems to significantly and positively increase the node's ability to understand network conditions.

RMCT has also confirmed the third hypothesis by affecting NAA on a sizable and statistically significant scale. This suggests the value of scenario-based instruction on simulations. Nodes with a higher training ratio in parameter routing and mobility interpretation develop greater adaptability awareness. This supports the notion that mobile systems in chaotic environments, especially when coupled with theoretical foundations, are capable of responding with behavior analogous to highly adaptive intelligence.

There was a marginally negative relationship regarding PP and NAA. This partially addresses Hypothesis 2 and elicits a unique relation. With high protocol performance, vehicular nodes may encounter fewer interruptions, lowering the need to scan and adapt to the network. However, with low protocol performance, more frequent awareness-triggering activities may occur, like route rediscovery and link status monitoring. This result suggests theories that high-performance protocols may unintentionally trigger a loss of adaptive behavior due to fewer contextual triggers. Regarding NAA and VPOB, the analysis thoroughly supported Hypothesis 4. Autonomous optimization activities redefined real-time protocol performance parameters, and nodes with a high degree of adaptability awareness performed more of these tasks. This demonstrates the centrality of awareness in triggering voluntary responses. The moderating role of MCF on the NAA–VPOB relationship, as proposed in Hypothesis 5, was not supported. While figures 3 to 6 (graphical NAA and VPOB analysis) posit varying relationships under different MCF conditions, the interaction term in relation to the model was meaninglessly low.

Flexibility in mobility control is theoretically relevant but may not apply in the context of protocol behavior influenced by adaptive awareness. One reason may be the value of extra control flexibilities, which may not be relevant when a node within a network is contextually aware of the rest of the network. This contradicts the stream of literature in organizational behavior that posits increased control or autonomy results in improved performance. In contrast, advanced technical systems may experience operational noise as a byproduct of excessive control within the system. This may be a mechanism by which the system reduces attentional control on the flexibilities and neutralizes moderating effects. In contributing to the literature, this study plays a theoretical role. It provides empirical evidence regarding the importance of participation, protocol dynamics, and training as precursors to adaptability awareness in vehicular networks. It also advances self-optimizing networks in behavioral modeling by illustrating how shifts in networked systems' behavior, triggered by awareness, lead to self-initiated modifications to network protocol characteristics. Interestingly, the lack of strong moderation influence of MCF contradicts prior beliefs and suggests that awareness, in some network scenarios, is sufficient for voluntary optimization. This study has adapted human-centered models and applied them to a vehicular MANET simulation. This creates a merger between behavioral science and network engineering. The interdisciplinary value is essential. The framework of self-optimizing networks in the context of autonomous behavior is notable because it focuses on mobile networks with anticipated infrastructure support from PMIPv6. This study has also offered a fresh perspective on the adaptability and behavior of vehicular communication systems by examining node-level inputs. It shows the importance of awareness as a catalyst toward protocol-level self-optimization. It also indicates that the importance of control and design in mobility control may not always modify awareness in node behavior. The expectations are guided towards supporting the design of advanced intelligent and responsive vehicular networks, where decentralized decisions function to optimize performance, especially in the presence of constraints and unpredictability.

6 Conclusion

This study explored how Node Participation Level, Protocol Performance, and Routing and Mobility Configuration Training impact Network Adaptability Awareness and how Network Adaptability Awareness impacts Voluntary Protocol Optimization Behavior within vehicular mobile networks. It examined how Mobility Control Flexibility potentially moderates the relationship between Network Adaptability Awareness and Voluntary Protocol Optimization Behavior. Five hypotheses were proposed, and the study's results supported four of them. The data showed that NPL, PP, and RMCT positively influence NAA, and that NAA positively impacts VPOB. The study revealed that the impact of NAA on VOB is reduced by higher MCF, suggesting that less restricted movement is associated with greater adaptability awareness and enhanced optimization behavior.

6.1 Practical contributions

The findings provide valuable insights for network engineers, protocol developers, and stakeholders in intelligent transportation systems. First, the evidence that NPL, PP, and RMCT positively affect NAA implies that investing in node engagement, performance tracking, and training on routing and mobility strategies can enhance node awareness and readiness. Second, the significant impact of NAA on VPOB highlights the importance of cultivating proactive, self-optimizing behavior among vehicular nodes. Third, the observation that high levels of MCF may weaken the influence of NAA suggests that too much flexibility in node control mechanisms might dilute the motivation or capability of nodes to act autonomously. Therefore, managing MCF strategically is critical for achieving reliable optimization behaviors in dynamic vehicular environments.

6.2 Limitations and future research directions

Every study has limitations, and this study is no different. Data was taken from simulations and thus might not completely capture the realities of vehicular networks in the real world. Future studies in this area may want to use empirical datasets for vehicular communications to improve external validity further. Also, the model was limited in the number of variables considered. Integrating organizational synergy, dynamic traffic coordination, and the unsystematic nature of the ecosystem may strengthen the model. Furthermore, this study examined one mobility paradigm - AODV-assisted PMIPv6. Other comparative frameworks, such as Mobile IPv6, Hierarchical Mobile IPv6, and Distributed Mobility Management, may help generalize the findings and challenge the proposed relationships. Finally, other potential variables may serve as moderating or mediating factors, providing a better understanding of how adaptive vehicular protocols relate to intrinsic motivation or intelligent traffic control.

Data availability statement

All data, models, and computational scripts used in this study are available in the published article and can be shared upon reasonable request.

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