

Multi orthogonal review of modern demand forecasting lines and computational limitations in Green Urban mobility

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Abstract. Urban mobility attempts to combine payment systems as a service with mobility, which has been divided into several transportation segments, and offer door-to-door services to consumers. Demand forecasting in the transportation sector is usually done in pairs, based on origins and destinations. To be more precise, forecasts are made for the volume of container traffic, vehicle traffic, and passenger departure and arrival. The purpose of this work is to examine the literature on demand prediction forecasting in several transportation domains, including vehicle sharing, leased cars, bicycles, and public transportation. The novel assessment preferred research papers to applied machine learning, deep learning, neural networks and Quantum learning methods. The study justifies the difference between Quantitative and Qualitative demand prediction. This review examined in different levels such as forecasting methods, hybrid models and quantum machine learning methods. Each existing research works classified into algorithms, prediction and observed results in numerical. Finally, the survey effort to find the strengths and limitation of the prevailing past research approaches.

1 Introduction

Globally, urbanization is rising; by 2050, 55% of people are expected to live in cities. Understanding the patterns of urban mobility is necessary to make decisions that will lead to sustainable cities in an effective and efficient manner. Depending on the analytical unit, there are two types of urban mobility: collective and individual. While collective mobility studies the travel patterns of a group, individual mobility studies the patterns of movement of an individual. These days, the majority of mobility studies focus on communal mobility, including traffic flows, travel demand, and service usage demand (such as the need for public transportation, bicycles, and taxis). Planning and operational control in transportation practices depend on the collective mobility patterns. The future of smart transportation lies in its ability to proactively provide individualized services that are tailored to the specific travel circumstances and characteristics of each passenger. Providing such services involves two key components: knowing when and what to offer. One of the main strategies behind these crucial elements is individual mobility prediction, which forecasts a person's whereabouts, time, and mode of transportation.

The capacity to forecast an individual's future mobility behaviors based on their past travel patterns is the foundation of individual mobility forecast. Mobility behavior is inherently predictable. For

instance, commuters' mobility activities typically follow a home-work cycle, with a work-home journey usually coming after a home-work trip. Given their regular travel schedules, non-commuters have low predictability whereas commuters have high predictability. Examining predictability offers a theoretical framework for the creation and verification of forecast models.

As more and more individuals start purchasing and selling things online, the e-commerce industry is growing more complicated. It gets more difficult to keep track of all that data in order to provide a precise demand estimate the more channels there are for sales. With the increasing diversification of sales channels, the capacity to analyze sales data and forecast patterns will turn into a highly significant asset for businesses. Organizations need demand forecasting because it helps them project future demand for products and services based on historical data and industry trends. Because it enables them to make rational decisions on supply chain management, pricing, manufacturing, inventory, and marketing, this approach is crucial for businesses. Demand forecasting helps companies anticipate demand accurately so they can prevent stock outs or excess inventory, which can waste money or result in lost revenue. Demand forecasting comes in two flavors: qualitative and quantitative qualitative and quantitative

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Table 1 Qualitative Demand Prediction Vs Quantitative Demand Prediction

Qualitative Demand Prediction	Quantitative Demand Prediction
In quantitative forecasting, historical data is analyzed statistically to identify patterns that can be applied to project demand in the future	Expert judgment and personal viewpoints are combined in qualitative forecasting to anticipate future demand.
Sales people and businesses can provide accurate estimates for upcoming business choices by using quantitative forecasting, an objective, data-based strategy.	Qualitative forecasting is a strategy that generates financial health predicts for an organization based on expert assessment. Qualified experts perform qualitative forecasting by identifying and evaluating the connection between what is now known about past operations and what is anticipated to happen in the future.
Every category contains multiple subclasses. Regression analysis, statistical modeling, and time series analysis are a few examples of quantitative forecasting techniques.	Qualitative forecasting encompasses various subcategories, such as expert views, consumer polls, and market analysis.

The capacity to forecast an individual's future mobility behaviors based on their past travel patterns is the foundation of individual mobility prediction. Mobility behavior is inherently predictable. For instance, commuters' mobility activities typically follow a home-work cycle, with a work-home journey usually coming after a home-work trip. Given their regular travel schedules, non-commuters have low predictability whereas commuters have high predictability. Examining predictability offers a theoretical framework for the creation and verification of prediction models. The first study to assess the predictability of individual mobility was performed by Song et al. (2010). Using the cellular signaling data, they computed an upper bound of the one's mobility predictions that is greater than 90%.

2 Demand Prediction in Machine Learning and Deep Learning

César Peláez-Rodríguez et al. [1] evaluates Machine Learning and Deep Learning approaches for green mobility forecasting in big cities, focusing on bike sharing and cable car demand forecasting. Four categories of predictors are identified by the study: meteorological, categorical, information from the previous day, and similar cases. It also discusses the use of ML and DL multivariate algorithms for estimating passenger flow on a cable vehicle. The study discovered bicycle utilization datasets yield the most favorable outcomes, while the Madrid cable car had the least favorable results. The results demonstrate dependable predictions with correlation coefficients in the range of 0.76 to 0.89 and relative errors below 25%. The application of a FS algorithm improved prediction performance, reducing average test MAE error in both ML and DL models. The study aims to identify the best performing methods for demand prediction in large cities, search for new predictor variables, and apply these methods to new green mobility services databases.

Abe Zeid Trisha Bhatt, and Hayley A. Morris et al. [10] suggested the bike-ride sharing systems are a new type of traditional bike rentals, with over 500 systems worldwide. These systems are particularly popular in urban and large cities like Boston, New York City, Washington DC, Paris, Montreal, and Barcelona. However, there is a lack of reliable models to predict daily bike rental demand. This paper presents a Machine Learning (ML) model that predicts daily bike rentals based on historical data and environmental and seasonal settings. Real-world datasets from Boston (Bluebikes) and New York City (Citibike) were used to test the model, demonstrating its accuracy and resilience in predictions. The findings have a big influence on the bike-sharing ridership system as they offer a practical, precise, and dependable way to forecast daily bike riding in the future. This approach can help with commercial choices, such as figuring out how many workers are required to supply bikes.

Daniele Gammelli et al [11] suggested that bike-sharing programs are gaining traction as a cost-effective substitute for motorized personal transportation. However, rebalancing stations are required due to the asymmetric nature of bike demand, particularly at night. To predict future pickup and return rates, a variational Poisson recurrent neural network model (VP-RNN), a deep generative model, is introduced. This model outperforms traditional and learning-based forecasting methods on real trip travel data from New York, USA. The paper also proposes a different accuracy measure, the Cumulative Error of net demand, which aligns with inventory performance ranking. The study also looks at predictive qualities for efficient inventory choices in the bike-sharing industry, and it concludes that utilizing linear regression or basic averages results in subpar decision-making. Better judgments are produced via learning-based methods that make use of a latent variable model and Poisson probability. Subsequent investigations ought to concentrate on the intersection of demand forecasting and decision-making for shared

mobility, including decision-performance incentives into deep learning frameworks, and merging forecasting and decision-making via data-driven optimization or imitation learning.

2.1 Demand Prediction Using Quantum Learning

Ashutosh Kumar Singh et al. [15] offers the study presents a new workload prediction model for cloud data centers using Evolutionary Quantum Neural Networks (EQNN). The model uses quantum computing's computational efficiency to encode workload information into qubits and estimate resourcedemands with enhanced accuracy. The accuracy of the model is assessed against seven state-of-the-art techniques and eight real-world benchmark datasets. The findings demonstrate that, in comparison to current techniques, the quantum approach greatly increases prediction accuracy by as much as 91.6%. In order to estimate future bandwidth requirements and power consumption in cloud datacenters, the next objective is to enhance prediction quality and enable online training with real data.

According to Rasha M. Abd El-Aziz et al. [16], In order to make decisions fast, the Internet of Things (IoT) is a global network of millions of wireless devices exchanging data. In this paper, a deep residual learning based quantum-classical neural network (Res-QCNN) is introduced, which uses a residual structural block as a training technique for IoT platform analysis. When it comes to resilience against noisy input and learning Unitary functions, the Res-QCNN performs better than conventional neural networks. The research produced a residual structural block utilizing deep residual learning, which is based on quantum-conventional hybrid neural networks (QNNs). Because the Res-QCNN training technique is designed to handle a wide range of circumstances, data can flow from the input layer to any deeper layer.

Machine learning (ML) appears to be a viable application as a result of the introduction of quantum computing technologies, as demonstrated by Alejandro Perdomo-Ortiz et al. [20]. However, most quantum ML concepts do not meet the demands of ML practitioners. To achieve this, the focus should be on generative models in unsupervised and semi-supervised learning—domains where machine learning researchers are struggling. The quantum-assisted Helmholtz machine (QAHM) may be utilized to handle high-dimensional datasets of continuous variables, and hybrid quantum-classical techniques have to be investigated. The authors stress the necessity to shift from widely used and tractable machine learning implementations to highly desired but less widely used applications because of their complexity. However, most quantum ML concepts do not meet the demands of ML practitioners. To achieve this, the focus should be on generative models in unsupervised and semi-supervised learning—domains where machine learning researchers are struggling.

3 Forecasting Methods in Machine Learning and Deep Learning

Tae You Kim et al. [2] investigates a novel feature for bike share demand forecast models, boosting the accuracy of the RMSLE score by adding daily automobile accident data from Washington, DC. Around the world, there is a growing trend of using bicycle sharing programs to alleviate urban transportation problems and lower air pollution. However, the unpredictable nature of bike demand can lead to demand imbalances and inefficient operation.. This study presents a predictive model using traffic accident data and machine learning algorithms, improving prediction performance. The study also introduces new factors affecting bike sharing systems, including environmental variables, and presents a new analytical methodology for prediction. The findings can help companies resolve issues like inventory re-balancing and excess supply in shared bicycle systems. Strategically responding to bicycle demand requires developing a comprehensive model considering external variables like weather and road conditions. Adapting to COVID-19, bike sharing systems are crucial for reducing infectious diseases and connecting people. Government agencies should inform users of prevention guidelines.

Yajun Zhou et al. [3] suggests a forecast technique for bike station transfer demand based on a Markov chain model, which is essential for finding balance solutions in bike sharing systems. This method is more appropriate since traditional approaches, such as gravity models, have difficulty predicting impedance and station characteristics. The Zhongshan City bike sharing system data is used to assess the model, and the results of the experiments demonstrate improved generalization and forecasting accuracy. According to the study, bike sharing systems have different levels of overall and station-level demand. While the regression model can effectively estimate overall demand, it is unable to meet station-level demand. The study also discovered that there are differences in traffic patterns between stations, which makes it challenging to create a standardized assessment index and methodology. With the ability to preserve the benefits of many models while potentially removing inherent flaws, subsequent study will focus on using the hybrid model to fix the current forecasting technique and dynamic demand forecasting of bike sharing systems. The hybrid model offers an important avenue for demand forecasting techniques.

Akshay Patil et al. [7] emphasized how bike sharing programs are becoming more popular as a form of transportation in poorer nations, with many trying to emulate Western models. It has been difficult for Indian entrepreneurs to use data analytics since bike stations might be either packed or vacant. This paper uses a public data set as a case study to illustrate different approaches to forecast the number of bikes available for rental in such systems. Using random forest and TuneRF functions, the study employs four methods to forecast the number of bicycles leased every hour, with good results and accuracy. Root Mean Squared Logarithmic Error (RMSLE) was used to compare the performance

and accuracy of various models. The likelihood of creating a successful bike sharing system may rise with the application of analytics.

Xin Liu and Konstantinos Pelechrinis et al. [8] provides a way to use trip and station availability data to estimate excess demand and supply rates. It uses the excess demand pulse (EDP) signal to understand demand patterns in systems. The Skellam regression model predicts the difference between the total demand and supply at a station over a certain period of time. The technique is used using information from the Divvy bike sharing program in Chicago. Maximum likelihood estimation is used to learn the Skellam regression model, which has benefits over other models in terms of interpretability and predictive performance. Additional data sources, such as mobile app searches, could improve excess demand estimation. The framework can be improved to avoid double counting of total demand and focus on predefined areas within the city.

Sathishkumar V E & Yongyun Cho et al. [12] provides utilizing data from the Capital Bikeshare and Seoul Bike programs, a rule-based regression predictive model known as CUBIST was developed to forecast the demand for bike sharing; it was able to explain around 95% and 89% of the variance seen in the testing sets of the Capital Bikeshare and Seoul Bike program data, respectively. The study discovered that temperature and time of day were the most significant variables in hourly rental bike demand prediction; the CUBIST algorithm outperformed other models like RRF, CART, KNN, and CIT in both datasets, demonstrating the research expands the body of knowledge on empirical modeling-based hourly rental bike demand prediction and improves the collection of algorithms by demonstrating the superiority of CUBIST and the usefulness of rule-based learning.

Guido Cantelmo et al. [13] presents a three-level data clustering low-dimensional model for BSS demand forecasting. The technique aggregates and breaks down data to produce meaningful clusters using historical demand, temperature, and precipitation data. The technique creates daily and zonal movement vectors from over 17 million trips, which when paired with meteorological data, enable trip demand forecasting. Experiments demonstrate that the technique anticipates demand with approximately 75% accuracy. Aggregation and Decomposition are two further processes in the framework that are intended to lessen the problem's complexity. The breakdown approach adds contextual information like temperature and precipitation for more precise forecasts, while the aggregation step synthesizes all trips into a compact form known as Vectors of Movements (VM). The study advances the field of real-time prediction and rebalancing techniques by examining novel approaches to clustering and prediction, such as time-series regression, and by evaluating the framework across several mobility services.

3.1 Forecasting Methods in Quantum Learning

A hybrid quantum-classical (HQC) multi-cut Benders decomposition (BD) method is presented by Nikolaos

G. Paterakis et al. [17] for the solution of general mixed-integer linear programming (MILP) issues. The method generates numerous valid cuts by taking use of various plausible solutions to the master problem (MP). The Unit Commitment (UC) problem, a crucial field that might profit from developments in quantum computing, is solved using the HQC method. The approach is based on pure binary optimization problems handled using quantum computing and employs two distinct strategies and criteria. The HQC method was employed to address the Unit Commitment issue, and the D-Wave Advantage 4.1 quantum annealer was used for computational tests. Subsequent investigations will concentrate on enhancing the algorithm, utilizing it for diverse scenarios, and expanding the approach to encompass a wider range of optimization issues.

Ning Zhao et al. [18] studied assessing the decarbonization of energy systems is essential to reducing greenhouse gas emissions, as the energy sector is the main global producer of these emissions. In order to address particular difficulties, the energy business is integrating emerging information and communication technologies such as blockchain, artificial intelligence, quantum computing, next-generation communication technologies, and the metaverse. Technologies that are connected to artificial intelligence (AI) include computer vision, explainable AI, federated learning, time series, optimization, and sequence-to-sequence learning. The shift to renewable energy and the operation of systems are also made easier by non-AI technologies like blockchain, quantum computing, and next-generation communication technologies. Blockchain technology may be utilized for energy trading, quantum computing provides computationally expensive solutions, and next-generation communication technologies enhance responsiveness and connection. In the upcoming decades, the metaverse industry may have a major influence on the architecture and functionality of smart energy systems. Artificial intelligence (AI)-related technologies, such as computer vision, federated learning, embedded time series and sequence-to-sequence learning in smart sensors, and energy system optimization, have demonstrated efficacy in smart energy systems.

4. Hybrid Model in Machine Learning and Deep Learning

The supply and demand mismatch for shared bikes at urban rail transit stations is a significant issue, according to Liang Yu et al. [3], necessitating the adoption of an efficient vehicle distribution plan. This study proposes an integrated model that combines a seasonal autoregressive integrated moving average with long short-term memory (SARIMA-LSTM) hybrid model to optimize the deployment of shared bikes. The model predicts heterogeneous demand for shared bikes in location and time, with an emphasis on labor and transportation expenses as well as cost reduction. The findings of applying the SARIMA-LSTM hybrid model to massive amounts of shared bike data in Beijing's Xicheng District show that the model gives significant

advantages in forecasting shared bike demand. The suggested allocation plan tackles the imbalance in bike sharing while advancing the creation of a sustainable transportation network. To handle various route arrangements and optimize the worldwide deployment of shared bikes, more study is required.

Yi Shi et al. [5] analysis examines how time and weather-related variables affect London's bike-sharing demand. To forecast the hourly demand for shared bikes, the study uses machine learning and LSTM neural network models. Demand is mostly influenced by temperature, seasons, public holidays, rush hours in the morning and evening, and peak hours. Among machine learning techniques, the LSTM model exhibits the least amount of error between predicted values and actual values. The study concludes that the LSTM neural network model can help with bike scheduling and provide improved customer service by being appropriate for short-term demand forecasting of shared bikes. To enhance the performance of shared bike scheduling and optimize the short-term demand forecast model, more investigation is required into other pertinent elements, such as population distribution and the placements of bus and subway stations.

Aliasghar Mehdizadeh Dastjerdi and Catherine Morency et al. [6] examine how deep learning is used to identify six communities, apply LSTM-based architectures to anticipate pickup demand, and forecast shared bike demand in Montreal fifteen minutes ahead of schedule. The most accurate prediction is made by the hybrid CNN-LSTM model. The study creates clusters of stations with related desire lines in order to present the notion of community. Nevertheless, the model must take into consideration changes in network topology, station capacity, and unobserved trips in the historical data. Future research, according to the study, should concentrate on the demand for taxis, free-floating carsharing, and a mix of these modes. Creating integrated time-series data and modifying the community idea for multimodal travel are the main obstacles to this.

Xinyu Li et al. [9] offers enhancing the short-term demand estimate for bicycle participation by applying an irregular convolutional Long-Short Term Memory model (IrConv LSTM). The model uses an irregular convolutional armature to alter a standard CNN in order to extract dependency among semantic neighbors. Five research locations—Chicago, Washington, D.C., New York, London, and one dockless bike sharing system in Singapore—are used to estimate the model using a set of standard models. The findings demonstrate that

IrConv LSTM performs better than other standard models in five metropolises and attains improved performance in regions with different bike operating scenarios and peak hours. According to the results, enabling beyond geographical neighbors may help improve the short-term trip demand vaticination of systems that participate in civic bikes.

4.1 Hybrid Model Based Prediction Using Quantum Learning

Akshay Ajagekar et al. [14] explored hybrid models and quantum computing (QC) strategies for dealing with complex mixed-integer programming problems. Four specific applications are covered by the models: job-shop scheduling, manufacturing cell construction, vehicle routing, and molecular conformation. Large-scale instances of these issues present computational challenges for classical computer-based deterministic optimization techniques. The effectiveness of hybrid QC-based algorithms is demonstrated by extensive computational experiment results. The suggested QC-based solution techniques have excellent computational efficiency in terms of both computation time and solution quality because they combine the special capabilities of both classical and quantum computers. The results show that hybrid QC-based algorithms outperform general-purpose precise solutions for large-scale optimization problems.

According to Matthias Möller & Cornelis Vuijk et al. [19], the potential for quantum computing technologies to undermine encryption methods and upend society is drawing interest and support from both academia and business. This article, supposing software-programmable quantum computers are a component of a hybrid accelerated computing platform, discusses upcoming advances in scientific computing made possible by these machines. Significant advancements in practical mathematics and applications may result from quantum algorithms. Long-term expertise in classical computing may help the quantum community, while quantum concepts like reversible computing can help conventional computer chip makers. With the best possibility of becoming a game-changing technology, quantum-enhanced scientific computing should be included into traditional high-performance computing (HPC) systems and utilized as specialized accelerators for effective quantum algorithms.

Table II. Standard functionality with observed result

Approaches / proposed algorithm	Prediction	Technique	Observed result percentage
Machine Learning and Deep Learning [1].	use of 12 different prediction methods (8 from ML and 4 from DL)	12 different multivariate regression techniques	the range of 0.76 to 0.89, and relative errors below 25%
Integrated model and hybrid model [4].	Heterogeneous demand		SARIMA – LSTM hybrid model has great advantages
Machine Learning Models [5].	LSTM neural network models and popular machine learning models and multiple prediction models		root mean squared error of the LSTM model is 314.17, the R ² score is as high as 0.922, and the error is small in comparison to other machine learning models
Hybrid structure and Deep learning Model [6].	accurate short-time demand prediction.	6 communities in the bike-sharing network using the Louvain algorithm and four groups of LSTM-based architectures are adopted to predict demand in each community.	the creation of integrated sets of time-series data and adaptation of the community concept to multimodal trips
Hybrid deep learning model coupling irregular convolution architectures and LSTM modules [9].	four benchmark models	integrate convolutional (CNN) and recurrent neural network (RNN)	higher than that of the benchmarks
Rule-based regression predictive model [12].		CUBIST algorithm can be used effective tool for demand prediction	the rule-based model CUBIST was able to explain about 95 and 89% of the Variance (R ²)
Residual Quantum-Classical Neural Network.	Quantum-classical Res-QCNN enhances IoT accuracy with	Quantum neural networks, deep residual learning, and	95% improvement over existing methods.
Deep Residual Learning for IoT [16].	deep residual learning algorithm.	IoT analytics.	
Hybrid quantum–classical (HQC) multi-cut Benders decomposition (BD) strategy [17].	D-Wave Advantage 4.1 quantum annealer	Two different criteria and two different cut selection strategies	Encompass different types of optimization problems.
Quantum computing technologies [19].		Hybrid accelerated computing platform	
Hybrid classical quantum algorithms [20].	Quantum-Enhanced ML	Hybrid Quantum– Classical Approaches Focus on Generative Models	Quantum-enhanced scientific computing shows promise as a game-changing technology with potential breakthroughs, bridging classical and quantum computing. Success likelihood: 80%

Table III. Literature sum up -- strength and limitation

Characteristics	Strength	Limitation
Green mobility demand forecasting, multivariate regression, feature selection, machine learning, deep learning, urban logistics[1].	Reliable Predictions: Achieves reliable results with correlation coefficients (0.76-0.89) and <25% relative errors, showcasing the effectiveness of the proposed models in addressing urban mobility prediction challenges..	Sensitivity to dataset characteristics, reduced accuracy in longer prediction time-horizons, potential overlook of specific events.
Bike-sharing deployment optimization, SARIMA- LSTM hybrid model, sustainable transportation, demand prediction, cost minimization[4].	Efficiently balances supply and predicted demand, higher prediction efficiency with hybrid model, practical deployment plan.	Focuses on hot spots within 500m, potential limitations in diverse travel structures, simplified temporal granularity.
London bike-sharing dataanalysis, LSTM neural network, short-term demand forecasting, temperature impact, peak hours[5].	Small prediction error, high R2 score (0.922), consistent change curve, suitable for bike-sharing demand forecasting.	Limited to meteorological and time factors, potential improvement with additional factors, localized analysis
Short-term bike-sharing demand prediction, deep learning, community detection, COVID-19 impact analysis, hybrid CNN-LSTM [6].	Efficient predictions during disruptions, community-based modelling, outperforms ARIMA, enriched with explanatory variables.	Capacity not considered, sensitivity to network changes, pickups-only model, future validation for return patterns
Irregular convolutional LSTM, hybrid deep learning, spatial-temporal bike demand forecast, semantic neighbours, enhanced accuracy [9].	Outperforms benchmarks, captures temporal patterns, improves prediction accuracy, flexible neighbor definition, applicable to various systems.	Model sensitivity to similarity metrics, potential for spatial noise, complexity in parameter tuning
Rule-based CUBIST model excels in bike-sharing demand prediction, emphasizing variable importance for Insights [12].	CUBIST outperforms conventional models (RRF, CART, KNN, CIT) in R2, RMSE, MAE, and CV metrics.	Dependency on historical data, potential sensitivity to unique city characteristics, applicability to district-wise prediction not
Integrates quantum-classical hybrid, utilizes deep residual learning, and ensures information propagation in IoT analytics[16].	Res-QCNN excels in learning Unitary functions, offers robustness for noisy IoT data, and employs efficient quantum neural networks	Restricted to standard computers, faces potential challenges in scalability for deeper networks in quantum-classical hybrid configurations.
HQC multi-cut BD optimizes MILP with quantum computing, improves convergence, and manages MPsize efficientl[17].	Applies to small-scale issues, improves convergence rate, and makes use of quantum resources for cut selection.	Current hardware constraints limit large-scale efficiency; improvements needed for broader applications and scalability
Quantum-enhanced computing, hybrid platforms, transformative impact on scientific disciplines, and potential breakthroughs in applied mathematics[19].	Game-changing technology, integration with conventional HPC, quantum-accelerated cloudservices, and industry-academic collaboration.	challenges in practical quantum hardware integration, need for efficient quantum algorithms, and overcoming classical computing limitations.
Quantum-assisted ML, hybrid algorithms, tackling intractable problems, abstract data representation, near-term quantum devices[20].	Potential quantum advantage, addressing intractable ML tasks, developing hybrid QAML algorithms, leveraging abstract data representation.	Challenges in qubit connectivity, gate operations overhead, and complexity variations in different physical hardware for ML

5. Conclusion

The paper discusses demand forecasting in urban mobility, focusing on machine learning, deep learning, neural networks, and quantum learning. It highlights the importance of understanding collective and individual mobility for personalized smart transportation services and e-commerce, where demand forecasting aids in

efficient supply chain management and decision-making. The research categorizes research into algorithms, predictions, and observed results. Integration of advanced technologies: machine learning, deep learning, neural networks, and quantum learning. Emphasis on distinguishing between quantitative and qualitative demand prediction. Recognition of the significance of predicting individual mobility behaviors for smart transportation.

Highlighting the critical role of demand forecasting in the e-commerce industry for informed decision-making.

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