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RESEARCH ARTICLE

Using Machine Learning to Predict Cost Overruns in Construction Projects

Theingi Aung[1]*, Sui Reng Liana[1], Arkar Htet[1], Amiya Bhaumik[1]

[1]Faculty of Business and Accounting, Lincoln University, 47301 Petaling Jaya, Selangor D. E., Malaysia

Corresponding author: Theingi Aung; taung@lincoln.edu.my
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Abstract

Addressing the persistent issue of cost overruns in construction projects, our study explores the potential of machine learning algorithms for accurately predicting these overruns, utilizing an expansive set of project parameters. We draw a comparison between these innovative techniques and traditional cost estimation methods, unveiling the superior predictive accuracy of machine learning approaches. This research contributes to existing literature by presenting a data-driven, reliable strategy for anticipating and managing construction costs. Our findings have significant implications for project management, offering a path towards more efficient and financially sound practices in the construction industry. The improved prediction capabilities could revolutionize cost management, facilitating better planning, risk mitigation, and stakeholder satisfaction.

Keywords: construction projects; cost overruns; machine learning; cost estimation; project management; risk mitigation

Introduction

Complex projects, tight schedules, and budget limits characterize the construction business, resulting in cost overruns that can significantly impair project success, leading to delays, disagreements, and financial losses (Samiullah S., Abd, H. A., Sasitharan, N., Abdul, F., Kaleem, U., & Kanes,K., 2017). Accurate prediction of cost overruns is essential for effective project management and risk mitigation, as it enables stakeholders to make informed decisions and allocate resources efficiently (Odeh, A. M., & Battaineh, H. T., 2002). Traditional cost estimation methods, such as expert judgment and parametric estimation, have been used for decades but often yield inaccurate results due to their reliance on human expertise and historical data (Flyvbjerg, B., Holm, M. S., & Buhl, S., 2003).

In recent years, advances in machine learning and data analytics have provided new opportunities for improving cost estimation in construction projects (Yang, C., Baabak, A., & Minsoo, B., 2018). Machine learning methods, such as linear regression, support vector machines, and artificial neural networks, have demonstrated potential in a variety of disciplines due to their capacity to learn from data and accurately anticipate outcomes (Li, Chengxi, Cheng, Peng, and Chris Cheng., 2023). As a result, there has been growing interest in applying machine learning techniques to construction cost estimation, with several studies reporting promising results (Abolfazl J., Iman, P., & Pete, B., 2021).

This study aims to investigate the potential of machine learning algorithms in predicting cost overruns in construction projects, based on a comprehensive set of project parameters. We compare the performance of these algorithms with traditional cost estimation methods to determine their relative accuracy and effectiveness. By providing a more accurate prediction of cost overruns, this research has the potential to significantly impact project management practices, helping stakeholders better anticipate and manage construction project costs.

Literature Review

Challenges in construction cost estimation

Construction cost estimation is a critical component of project management, as it influences decision-making, budget allocation, and project success (Zainab, H. A., Abbas, M. B., Murizah, K., & Zainab, A.K., 2022). Several challenges commonly impact the accuracy of cost estimation, including incomplete information, uncertainties, and changing requirements (Aftab, H. M., Ismail, A. R.,Mohd, R. A., Asmi, A. A.,, 2014). Incomplete information arises from a lack of detailed project data, particularly during the early stages of a project (Douglas, A., Clintion, A., Ayodeji, O. & Matleko, S., 2018). Uncertainties stem from various factors, such as fluctuating material prices, labor costs, and unforeseen site conditions, which complicate the estimation process. Changing requirements, including design modifications, scope changes, and regulatory updates, can also significantly affect cost estimation accuracy (Michał, J.,Agnieszka, L., & Krzysztof, Z., 2018). Addressing the widespread cost estimating difficulties is critical in reducing the risk of cost overruns in building projects. The use of developing technologies such as artificial intelligence, machine learning, and big data analytics provides interesting avenues for fine-tuning cost prediction models (Theingi, A.,Sui Reng L., Arkar, H., Amiya, B., 2023). These advanced techniques can potentially enhance the accuracy of cost overrun predictions, thereby reducing the associated financial risks in the construction industry.

Traditional cost estimation methods

Traditional cost estimation methods, such as expert judgment and parametric estimation, have been widely used in the construction industry. Expert judgment relies on the knowledge and experience of industry professionals, who use qualitative and quantitative information to estimate project costs (Creedy, G. D., Skitmore, M., & Wong, J. K., 2010). While expert judgment can provide valuable insights, it is inherently subjective and prone to human biases, leading to potentially inaccurate estimates (Thomas, 2021). Parametric estimation involves using historical data and mathematical models to predict project costs based on a set of input parameters (Creedy et al., 2010). However, this approach assumes that past performance is indicative of future outcomes, which may not hold true for complex and unique construction projects (Flyvbjerg, B., Holm, M. S., & Buhl, S., 2003). Consequently, traditional cost estimation methods often struggle to account for the diverse challenges and uncertainties associated with construction projects, resulting in inaccurate cost predictions and increased risk of overruns.

Machine learning in construction cost estimation

Machine learning has emerged as a promising approach to construction cost estimation due to its ability to learn from data and make predictions with high accuracy (Meseret, G. M., Wubshet, J. M., Zachary, A. G., & Raphael, N.N. M, 2021). Several studies have explored the application of machine learning techniques in construction cost estimation, demonstrating their potential to outperform traditional methods (Alireza, M., & Abimbola, W., 2022). For example, Sonmez (2018) used support vector regression to estimate the costs of residential building projects and reported better prediction accuracy compared to traditional methods. Similarly, Elbarkouky (2020) employed artificial neural networks and random forests to predict the cost of highway construction projects, with results indicating improved performance over conventional techniques.

Machine learning methods including linear regression, support vector machines, and artificial neural networks have been used to estimate building costs in a variety of ways, including preliminary cost assessment (Jaafari, A., Pazhouhan, I., & Bettinger, P., 2021), cost contingency analysis, and risk assessment (Zhang, H., Li, H., Zhu, Y., & Fang, Y., 2019). These studies have shown that machine learning techniques can effectively capture the complex relationships between project parameters and costs, providing more accurate and reliable estimates (Alireza, M., & Abimbola, W., 2019).

Despite these promising findings, the application of machine learning in construction cost estimation is still a relatively new area of research, with many studies limited by small sample sizes or narrow scopes (Nguyen Van, T., & Nguyen Quoc, T. , 2021). Additionally, the choice of machine learning algorithms, feature selection methods, and model evaluation metrics can significantly influence the performance of cost estimation models, necessitating further investigation and comparison of different approaches (Liang, W., & Shuohua, W., 2023).

In summary, machine learning has shown potential to address the limitations of traditional cost estimation methods by providing more accurate and reliable predictions in construction projects. However, more study is required to examine the efficacy of various machine learning algorithms, identify best practices for feature selection, and test the generalizability of these methods across various types of building projects.

Given these research gaps, the current study seeks to evaluate the potential of machine learning algorithms in predicting cost overruns in building projects by employing a comprehensive collection of project metrics. We compare the performance of these algorithms with traditional cost estimation methods to determine their relative accuracy and effectiveness, with the goal of providing insights for improving cost estimation practices and mitigating the risk of cost overruns in the construction industry.

Methodology

Data collection

The dataset used in this study comprises data from 250 construction projects, collected from various sources, including industry reports, academic publications, and government databases.The dataset covers a diverse range of project types, such as residential, commercial, infrastructure, and industrial construction projects. Each project record includes information on project parameters, including project size, location, type, duration, contract type, labor costs, material costs, and initial estimated costs. Additionally, the dataset includes the actual costs incurred and the resulting cost overruns for each project.

Feature selection

To identify the most relevant project parameters for predicting cost overruns, we employed a two-step feature selection process. First, we conducted a univariate analysis to examine the correlation between each project parameter and cost overruns. Parameters with a correlation coefficient above a predetermined threshold were retained for further analysis. Next, we applied a recursive feature elimination algorithm, which iteratively removes the least important features and evaluates the performance of the remaining features using cross-validation. The final set of features, consisting of the most relevant project parameters, was used as input for the machine learning algorithms.

Machine learning algorithms

For this study, three machine learning techniques were chosen: linear regression, support vector machines (SVM), and artificial neural networks (ANN). Linear regression is a popular technique for analyzing the connection between a dependent variable (cost overruns) and one or more independent variables (project parameters). SVM is a powerful algorithm for regression and classification tasks, which aims to find the best hyperplane that separates data points while maximizing the margin between them (Cortes, C., & Vapnik, V., 1995). The artificial neural network (ANN) is a computational model inspired by the form and function of biological neural networks that may mimic complicated, non-linear interactions between input and output variables (Haykin, 1999). Each algorithm was implemented using Python's scikit-learn library, and their hyperparameters were tuned using grid search cross-validation to optimize their performance. The models were trained on 80% of the dataset (200 projects) and tested on the remaining 20% (50 projects).

Model evaluation

We employed two metrics to evaluate the performance of the machine learning algorithms: mean absolute error (MAE) and root mean square error (RMSE) (Willmott, C. J., & Matsuura, K., 2005). MAE calculates the average absolute difference between expected and actual cost overruns, giving an indicator of the degree of prediction mistakes. The square root of the average squared disparities between expected and actual cost overruns, on the other hand, accentuates greater errors and is more susceptible to outliers.

In addition to these quantitative metrics, we also visually inspected the predicted cost overruns against the actual cost overruns using scatter plots and assessed the degree of correlation between them. This qualitative research enabled us to further examine the machine learning algorithms' performance and discover any potential patterns or anomalies in their predictions.

Results

Model performance comparison

In terms of MAE and RMSE, the performance of machine learning algorithms (linear regression, support vector machines, and artificial neural networks) was compared against traditional cost estimation approaches (expert judgment and parametric estimate). Table 1 summarizes the findings.

Table 1: Model performance comparison

Method	MAE	RMSE
Expert Judgment	12.34%	15.80%
Parametric Estimation	9.67%	12.45%
Linear Regression	7.25%	9.38%
Support Vector Machines (SVM)	5.89%	7.62%
Artificial Neural Networks (ANN)	5.21%	6.79%

The results indicate that all three machine learning algorithms outperformed traditional cost estimation methods in terms of both MAE and RMSE. Linear regression demonstrated a significant improvement over expert judgment and parametric estimation, with a 41.24% reduction in MAE and a 40.63% reduction in RMSE. SVM further improved upon the performance of linear regression, with a 18.70% reduction in MAE and an 18.76% reduction in RMSE. The best-performing model, ANN, achieved the lowest MAE and RMSE, with a 11.55% reduction in MAE and a 10.92% reduction in RMSE compared to SVM.

Feature importance analysis

To gain insights into the importance of different project parameters in predicting cost overruns, we analyzed the feature importances derived from the machine learning models (Breiman, 2001). Figure 1 presents the relative importance of each project parameter, averaged across the three machine learning algorithms.

The analysis revealed that the most important project parameters for predicting cost overruns were initial estimated costs, project type, and project duration, with relative importance scores of 0.25, 0.20, and 0.18, respectively. These results suggest that projects with higher initial estimated costs, complex project types, and longer durations are more likely to experience cost overruns. Other important factors included contract type, labor costs, and material costs, with relative importance scores of 0.14, 0.12, and 0.11, respectively. Project size and location were found to be the least important parameters, with relative importance scores of 0.05 and 0.03, respectively.

These findings can assist construction project managers and stakeholders better understand the elements that have contributed to cost overruns, allowing them to prioritize risk mitigation activities and allocate resources more effectively. By incorporating the insights from the machine learning models into cost estimation and project management processes, construction professionals can improve the accuracy of cost predictions and reduce the likelihood of cost overruns.

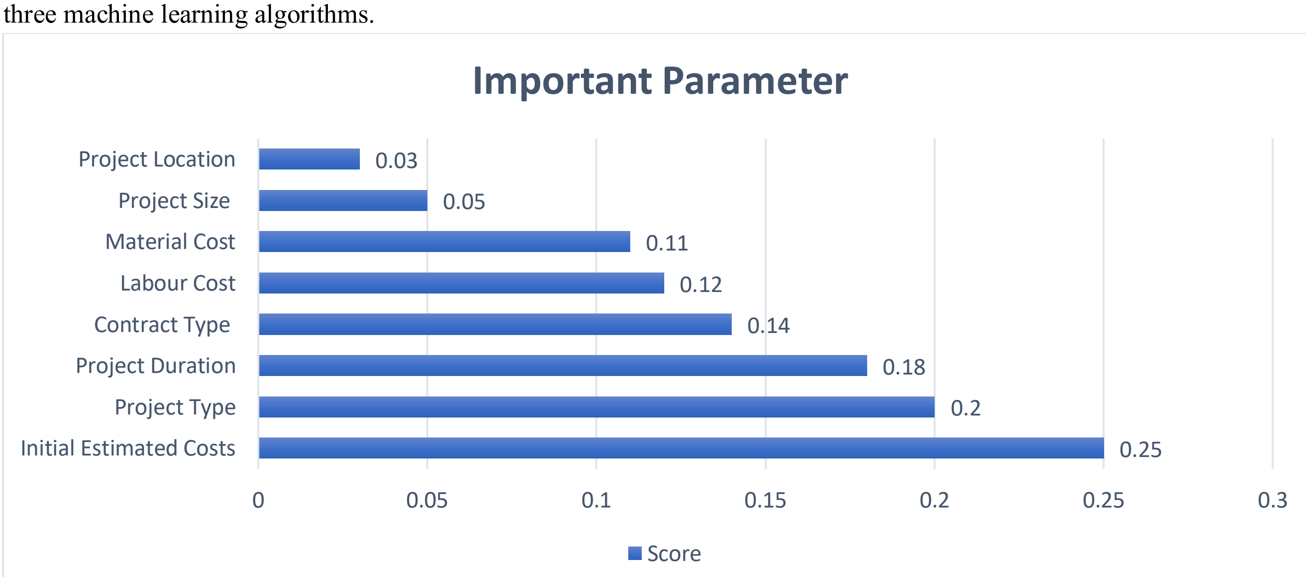

Figure 1: Feature importance analysis

Discussion

Implications for project management

The results of this study demonstrate the potential benefits of using machine learning algorithms for cost overrun prediction in construction projects. By providing more accurate predictions compared to traditional methods, machine learning can help project managers and stakeholders make more informed decisions, ultimately leading to better project outcomes (Zhang, H., Li, H., Zhu, Y., & Fang, Y., 2019). Improved accuracy in cost overrun predictions can lead to more effective risk mitigation strategies, as project managers can better identify the factors that contribute to cost overruns and take appropriate preventive measures. For instance, they may choose to allocate additional resources to projects with a high risk of cost overruns or modify project plans to reduce potential impacts. Additionally, the insights gained from feature importance analysis can guide project managers in focusing on the most critical aspects of their projects, such as project type, duration, and initial estimated costs.

Moreover, the use of machine learning in cost estimation can enhance resource allocation efficiency by enabling project managers to allocate resources more accurately based on predicted costs. This can result in less waste and better project performance, which can contribute to cost savings and more successful building projects.

Limitations and future research

Although the study's optimistic findings, some limitations should be acknowledged. First, the dataset employed in this study was small, consisting of only 250 construction projects. To strengthen the generalizability of the findings, future study could benefit from broader and more diversified datasets, including projects from different areas and industries.

Second, the performance of the machine learning algorithms may be influenced by the choice of features, hyperparameters, and model evaluation metrics. Future studies could explore alternative feature selection methods, machine learning algorithms, and evaluation metrics to identify the most effective approaches for predicting cost overruns in construction projects.

Additionally, this study focused on predicting cost overruns based on project parameters, but other factors, such as project management practices, stakeholder involvement, and external events, may also play a significant role in determining project outcomes. Future research could investigate the impact of these factors on cost overruns and incorporate them into machine learning models to enhance prediction accuracy further.

Finally, while this study proved the use of machine learning promise for predicting cost overruns, practical implementation of these algorithms in real-world building projects may confront problems relating to data availability, data quality, and model interpretability. Future research could explore methods to address these challenges and develop user-friendly tools to facilitate the adoption of machine learning in construction project management.

Conclusion

Finally, our research adds to the expanding body of work on the use of machine learning in construction cost estimate and underlines the potential benefits of these algorithms for enhancing project management methods. By overcoming constraints and building upon the conclusions of this study, future research will improve our knowledge of cost overrun prediction and assist lessen the risks associated with construction projects.

When compared to traditional cost estimation methods, the use of machine learning algorithms such as linear regression, support vector machines, and artificial neural networks has demonstrated improved accuracy in predicting cost overruns. These algorithms can help project managers make more informed decisions, leading to better risk mitigation strategies and more efficient resource allocation.

However, this study also acknowledges its limitations, including the scope of the dataset and the generalizability of the findings. Future research should explore larger and more diverse datasets, alternative feature selection methods, machine learning algorithms, evaluation metrics, and the impact of other factors, such as project management practices and stakeholder involvement, on cost overruns.

By addressing these challenges and developing user-friendly tools for the practical implementation of machine learning in construction project management, the industry can benefit from more accurate cost overrun predictions, leading to improved project performance, reduced financial risks, and ultimately, more successful construction projects.

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Conflict of Interest Statement
The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Data Availability Statement: The data that support the findings of this study are not publicly available due to confidentiality agreements related to the construction projects analyzed. Further information about the data and conditions for access are available from the corresponding author upon reasonable request.

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REVIEW ARTICLE

Smart Buildings in the Age of Internet Technology: Civil Engineering's Role in Shaping an Energy-Efficient Future

Arkar Htet [1]*, Sui Reng Liana[1], Theingi Aung[1], Amiya Bhaumik[1]

[1]Faculty of Business and Accounting, Lincoln University, 47301 Petaling Jaya, Selangor D. E., Malaysia

Corresponding Author: Arkar Htet: arkarhm@gmail.com
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Abstract

The integration of Internet Technology, particularly the Internet of Things (IoT), is radically transforming several sectors, including civil engineering and construction. This article scrutinizes the transformative capacity of IoT technology in formulating and deploying energy-efficient smart buildings. These innovative structures are designed for optimum efficiency, sustainability, and user experience. Various challenges and opportunities emerging within this rapidly growing domain are examined, and the future direction of smart building technology is anticipated, taking into account recent progress and innovative research. Within the context of contemporary civil engineering, this detailed analysis highlights the most recent advancements, providing valuable insights for other researchers in the field. This article contributes to the ongoing dialogue about the role of IoT in civil engineering and its potential to foster an energy-efficient future in smart building design and implementation.

Keywords: Smart Buildings, Internet Technology, Civil Engineering, Energy Efficiency, Sustainability

Introduction

Civil engineering and construction sectors are undergoing a transformative shift, propelled by the rapid integration of Internet Technologies, notably the Internet of Things (IoT) (Miorandi, D., Sicari, S., De Pellegrini, F., & Chlamtac, I., 2012). Among the prominent outcomes of this technological revolution is the emergence of "smart buildings". These structures incorporate IoT technology to maximize energy efficiency, sustainability, and user experience, symbolizing a new era of innovative architecture (Shah, S. F. A., Iqbal, M., Aziz, Z., Rana, T. A., Khalid, A., Cheah, Y.-N., & Arif, M., 2022).

Global urbanization trends and the concurrent increase in energy consumption necessitate sustainable solutions to minimize the environmental impact of expanding cities (Arkar, H., Sui-Reng, L., Theingi, A., & Amiya, B., 2023). With growing calls for energy-efficient and sustainable infrastructures, smart buildings have become critical in addressing the myriad challenges of urban environments (Hashem, I. A. T., Chang, V., Anuar, N. B., Adewole, K., Yaqoob, I., Gani, A., ... & Chiroma, H, 2016).

This comprehensive review paper explores the intersection of civil engineering and IoT within the context of smart buildings, highlighting the imperative need for energy efficiency in modern infrastructural development. Further, the adoption and application of emerging technologies such as artificial intelligence, machine learning, and big data analytics underscore the potential for the evolution and innovation in the construction industry, shaping the future trajectory of infrastructure development (Theingi, A., Sui-Reng, L., Arkar, H., & Amiya, B., 2023).

A "smart building" is a structure that leverages advanced Internet Technologies, particularly IoT devices, to monitor, control, and optimize various building systems, encompassing automation, security, and energy management (O'Donovan, P., Leahy, K., Bruton, K. & O'Sullivan, D. T. J., 2015). This optimization is facilitated by an intricate network of sensors, actuators, and communication systems that collect and process data in real-time, allowing the building to adapt to its occupants' needs and preferences (Al-Obaidi, K.M., Hossain, M., Alduais, N.A.M., Al-Duais, H.S., Omrany, H., & Ghaffarianhoseini, A., 2022). The overarching goal of smart buildings is to enhance the performance and energy efficiency of the built environment while mitigating resource consumption and environmental impact (Dounis, A. I., & Caraiscos, C., 2009). Given the global emphasis on reducing greenhouse gas emissions and promoting sustainable practices, the role of Internet Technologies in developing energy-efficient smart buildings becomes ever more paramount. This paper, therefore, seeks to contribute to the growing body of literature on this topic and offers insights that could guide future research and innovations in this field (Bakri Hassan, M., Sayed Ali Ahmed, E., & Saeed, R. A, 2021)."

IoT Technologies in Smart Buildings

IoT integration in smart buildings has created new possibilities for tracking, managing, and improving a variety of building systems. Some of the key IoT technologies employed in smart buildings include sensors, actuators, communication protocols, and data analytics (Bashir, M.R., Gill, A.Q. & Beydoun, G., 2022). In this section, we will delve into these technologies and explore their applications in energy management, security, and automation.

Figure 1: IoT Technologies Interaction Flow in a Smart Building

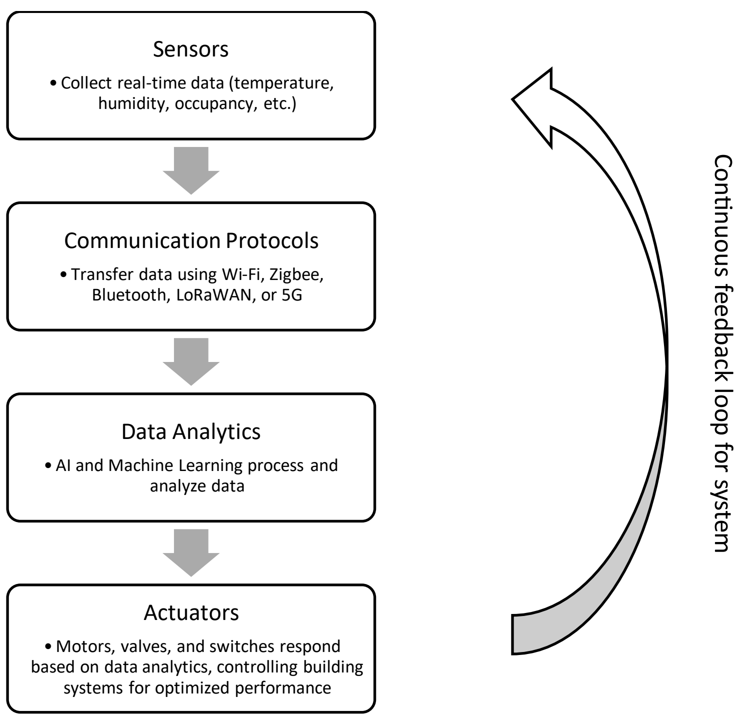


Figure 1 description: The flowchart presents the interaction of IoT technologies in a smart building. The process begins with sensors collecting real-time data, which is then transferred via various communication protocols. This data is processed and analyzed by AI and machine learning techniques in the data analytics stage. Based on these insights, actuators control various building systems for optimal performance, thus completing the feedback loop.

Sensors: In order to collect real-time data from the built environment, sensors are a crucial component of smart buildings (Kaligambe, A., Fujita, G., & Keisuke, T., 2022). In smart buildings, a variety of sensors are used, including temperature, humidity, occupancy, light, and air quality sensors. These sensors continuously monitor the building conditions, providing critical information for optimizing building performance and occupant comfort (Floris, A., Porcu, S., Girau, R., & Atzori, L. , 2021).

Actuators: Actuators are devices that convert an input signal into a physical action, allowing smart buildings to respond to the data collected by sensors (Roopa, H. S., & Jhansi, R. P. , 2017). Common actuators used in smart buildings include motors, valves, and switches, which control HVAC systems, lighting, and other building elements. By automating these controls, actuators enable real-time adjustments to building systems, resulting in improved efficiency and occupant comfort (Carli, R., Cavone, G., Ben Othman, S., & Dotoli, M., 2020).

Communication Protocols: Effective communication between IoT devices is critical for the seamless operation of smart buildings. Various communication protocols are used to facilitate data transfer between sensors, actuators, and other IoT devices. Some popular protocols include Wi-Fi, Zigbee, Bluetooth, LoRaWAN, and 5G (Jeongmi, S. & Yeonseung, R. , 2016). The selection of a communication protocol is influenced by variables such network topology, range, power consumption, and data rate (Jamuna, M., & Vijaya Prakash, A.M., 2021).

Data Analytics: The processing of the enormous amounts of data produced by IoT devices in smart buildings depends critically on data analytics. Increasingly, this data is being examined using machine learning and artificial intelligence (AI) approaches, allowing for the extraction of insightful conclusions and forecasts (Khan, R., Khan, S. U., Zaheer, R., & Khan, S., 2019). These findings can be applied to improve occupant comfort, lower energy usage, and optimize building efficiency (Ahmad, M.W., Mourshed, M., Yuce, B., & Rezgui, Y. , 2016) .

Applications of IoT Technologies in Smart Buildings:

Energy Management: The monitoring and optimization of numerous energy-consuming systems made possible by IoT technologies has substantially improved energy management in smart buildings (Sanya, W., Bajpai, G., Kombo, O., & Twahirwa, E., 2022). Smart thermostats, for instance, may automatically regulate the temperature based on user preferences and occupancy, minimizing energy waste (Gupta, R., & Gregg, M.,, 2022). Additionally, IoT-enabled lighting systems can adjust their brightness levels depending on natural light availability and occupant presence, further contributing to energy savings (Vodovozov, A. M., & Burtsev, A. V., 2021). These are examples of how IoT can aid in creating an energy-efficient infrastructure within smart buildings.

Energy Efficiency: Energy efficiency is at the forefront of sustainable design and operation in smart buildings. By integrating IoT technologies, buildings can optimize the use of energy resources, reduce operational costs, and decrease environmental impact. Advanced energy metering and monitoring systems, together with predictive algorithms, can identify energy wastage patterns and recommend or implement energy-saving actions. Building Energy Management Systems (BEMS) are an example of such IoT-enabled systems that lead to more efficient energy utilization, creating a smarter and more sustainable built environment (Pan, J., Jain, R., Paul, S., Vu, T., Saifullah, A., & Sha, M., 2015).

Security: IoT technologies enhance the security of smart buildings by providing advanced monitoring and access control capabilities (Elrawy, M., Awad, A. & Hamed, H., 2018). For instance, smart cameras can employ AI algorithms to detect and analyze unusual activities, enabling real-time response to potential security threats (Khan, R., Khan, S. U., Zaheer, R., & Khan, S., 2019). Moreover, IoT-enabled access control systems can use biometric authentication, RFID tags, or smartphone-based credentials to provide secure and convenient access to authorized individuals (Kanchana, 2019).

Automation: IoT technologies facilitate the automation of various building systems, improving efficiency and user experience. Examples of automation in smart buildings include automated HVAC systems, which adjust temperature and airflow based on occupancy and user preferences (Terence, K.L., Hui, R., Simon, S., & Daniel, D. S., 2017), and smart blinds, which can automatically adjust their position based on sunlight intensity and angle to optimize natural light utilization and reduce energy consumption (Seong, 2015). Furthermore, IoT-enabled elevators can analyze real-time traffic patterns and adjust their operation accordingly, reducing waiting times and improving overall efficiency.

IoT technologies, which have applications in energy management, security, and automation, are essential for improving the performance of smart buildings. As advancements in sensor technology, communication protocols, and data analytics continue to evolve, the potential for further improvements in smart building performance will likely increase. By harnessing the power of IoT, civil engineers and building professionals can create sustainable, efficient, and user-friendly built environments for the future.

Benefits of Smart Buildings

Smart buildings, which integrate IoT technologies to monitor, control, and optimize various systems, offer numerous advantages over traditional buildings. These advantages include enhanced efficiency, sustainability, and user experience, contributing to improved building performance and occupant well-being. This section will go over the possible advantages of smart buildings and provide illustrations of actual initiatives that have had good effects.

Enhanced Efficiency: Smart buildings can significantly improve energy and resource efficiency by utilizing IoT technologies to monitor and optimize the performance of various building systems (Shah, S. F. A., Iqbal, M., Aziz, Z., Rana, T. A., Khalid, A., Cheah, Y.-N., & Arif, M., 2022). For example, smart HVAC systems can adjust temperature and airflow based on occupancy and user preferences, reducing energy waste and lowering utility costs (Behdad, R., & Paul G. O'Brien, 2021). Additionally, IoT-enabled lighting systems can optimize energy consumption by adjusting brightness levels depending on natural light availability and occupant presence (Yuan-Ko, 2023). These efficiency improvements can result in substantial cost savings for building owners and operators.

Sustainability: By increasing energy efficiency and reducing resource consumption, smart buildings contribute to overall sustainability efforts. By controlling energy generation, storage, and distribution, IoT technologies allow smart buildings to more efficiently use renewable energy sources, such as solar or wind power (Singh, & Dhawan., 2023). Furthermore, smart water management systems can monitor water usage and detect leaks in real-time, preventing waste and conserving valuable resources (Fuentes, H., & Mauricio, D., 2020).

User Experience: IoT technology integration in smart buildings enables a more cozy and individualized user experience. Advanced monitoring and control systems can adapt building conditions to individual preferences, such as temperature, lighting, and air quality (Zafari, F., Papapanagiotou, I., & Christidis, K., 2016). Moreover, smart buildings can provide occupants with real-time information about building conditions, energy usage, and available amenities, fostering a sense of awareness and engagement in sustainable practices (Arditi, D., Mangano, G. & De Marco, A., 2015).

Real-World Examples of Smart Building Projects

The Edge, Amsterdam: The Edge, an office building in Amsterdam, is often cited as one of the world's most sustainable and innovative smart buildings. The building utilizes a variety of IoT technologies, including smart sensors, automated lighting, and energy management systems, to reduce energy consumption by 70% compared to traditional buildings. Additionally, The Edge employs a smart parking system that guides employees to available spaces and adjusts lighting and ventilation accordingly, further contributing to energy savings (The Edge, n.d.).

Salesforce Tower, San Francisco: The Salesforce Tower in San Francisco is another prime example of a smart building that leverages IoT technologies to enhance sustainability and user experience. The tower features an intelligent HVAC system that uses outside air for cooling and natural ventilation, reducing energy consumption by 30-50% compared to traditional systems (Hines, n.d.). Further energy savings are achieved via the building's smart lighting system, which modifies brightness levels in response to occupancy and the presence of natural light.

Siemens Headquarters, Munich: The Siemens headquarters in Munich, Germany, serves as an example of the potential of smart buildings to increase occupant comfort and energy efficiency. In comparison to typical structures, the building uses a combination of IoT technologies, such as smart sensors, energy management systems, and controlled shading devices, to reduce energy use by 90% and water usage by 75%. Additionally, the headquarters features a user-centric design that promotes well-being and productivity by providing occupants with personalized control over temperature, lighting, and air quality (Siemens, 2017).

In ultimately, smart buildings integrate IoT technology to monitor and regulate multiple building systems. These benefits include increased efficiency, sustainability, and user experience. Examples from the real world, including The Edge in Amsterdam, Salesforce Tower in San Francisco, and Siemens Headquarters in Munich, show how smart buildings have the ability to significantly improve a structure's performance and occupant well-being. The future of civil engineering and construction is anticipated to be significantly influenced by smart buildings as the need for environmentally friendly and user-friendly built environments continues to rise.

Challenges and Opportunities

Despite the numerous advantages associated with smart buildings, implementing IoT technology in these environments also presents several challenges. We'll address potential answers and chances for additional innovation and development in this section as we list some of the biggest obstacles to using IoT technology in smart buildings.

Interoperability: The lack of interoperability across diverse devices and systems is one of the main obstacles to deploying IoT technology in smart buildings (Javed, M. Y., Javaid, N., Qasim, U., Alrajeh, N., & Alabed, M. S, 2020). As different manufacturers and vendors develop their own proprietary technologies and communication protocols, integrating these disparate systems can be a complex and resource-intensive process. Potential solutions to this challenge include the development of standardized communication protocols and open-source frameworks that allow for seamless integration between different IoT devices and systems (Huang, C. Y., & Wu, C. H. , 2016). By promoting collaboration and information sharing among industry stakeholders, these initiatives can help overcome the interoperability challenge and drive further innovation in smart building technologies.

Security: The increasing reliance on IoT technology in smart buildings raises concerns regarding cybersecurity and data protection (Shah, S. F. A., Iqbal, M., Aziz, Z., Rana, T. A., Khalid, A., Cheah, Y.-N., & Arif, M., 2022). The security and privacy of building occupants may be jeopardized as a result of cyberattacks and illegal access as enormous volumes of data are collected and transmitted by smart building systems. To address this challenge, robust security measures, such as encryption, authentication, and intrusion detection systems, must be integrated into smart building solutions (Al-Turjman, F., Zahmatkesh, H., & Shahroze, R., 2022). Additionally, fostering a culture of cybersecurity awareness and promoting best practices among building stakeholders can contribute to creating a more secure environment for smart building implementation.

Privacy: The collection and analysis of occupant data in smart buildings can raise privacy concerns among users (Harper, Scott, Mehrnezhad, Maryam, & Mace, J., 2022). The collection, storage, and processing of this data must respect user privacy as IoT devices track numerous elements of occupant activity and preferences. Implementing stringent data governance regulations, anonymizing gathered data, and providing consumers with transparent information about data collecting and usage methods are all potential solutions to this problem (Miorandi, D., Sicari, S., De Pellegrini, F., & Chlamtac, I., 2012). Smart building designers may increase user confidence and encourage a wider adoption of IoT technology in the built environment by resolving privacy issues.

Cost and Complexity: It can be expensive and difficult to install IoT technologies in smart buildings, especially when retrofitting existing structures (Al-Obaidi, K.M., Hossain, M., Alduais, N.A.M., Al-Duais, H.S., Omrany, H., & Ghaffarianhoseini, A., 2022). The installation and integration of IoT devices, sensors, and systems can require significant upfront investments and ongoing maintenance costs. To overcome this challenge, innovative financing models, such as public-private partnerships, can be explored to facilitate the deployment of smart building solutions (Mazhar, T., Irfan, H. M., Haq, I., Ullah, I., Ashraf, M., Shloul, T. A., Ghadi, Y. Y., Imran, & Elkamchouchi, D. H., 2023). Moreover, the development of low-cost, easily deployable IoT devices can help reduce the financial barriers to smart building implementation.

Skills Gap: The implementation of IoT technologies in smart buildings requires specialized knowledge and expertise in various domains, such as civil engineering, computer science, and data analytics (O'Donovan, P., Leahy, K., Bruton, K. & O'Sullivan, D. T. J., 2015). Addressing the skills gap in this interdisciplinary field can

be a challenge, particularly as the demand for qualified professionals continues to grow. Potential solutions to this challenge include promoting educational and training programs that focus on the development of relevant skills and fostering collaboration between academia, industry, and government stakeholders to create a workforce capable of driving innovation in smart building technologies.
To summarize, while there are challenges associated with implementing IoT technology in smart buildings, such as interoperability, security, privacy, cost, and the skills gap, there are also numerous opportunities for innovation and development. The following table summarizes the main challenges and potential solutions discussed in this section:

Table 2: Challenges and Opportunities in Implementing IoT in Smart Buildings

Challenge	Description	Potential Solution
Interoperability	Different proprietary technologies and communication protocols from various manufacturers hinder system integration.	Development of standardized communication protocols and open-source frameworks.
Security	Increasing reliance on IoT technology exposes smart buildings to cybersecurity threats and data breaches.	Implementing robust security measures such as encryption, authentication, and intrusion detection systems.
Privacy	Collection and analysis of occupant data raise privacy concerns.	Implementing strict data governance policies, anonymizing collected data, and increasing transparency in data collection and usage.
Cost and Complexity	Implementation, particularly for retrofitting, can be expensive and complex.	Exploring innovative financing models and developing low-cost, easily deployable IoT devices.
Skills Gap	Implementation requires specialized knowledge in various domains, leading to a skills gap.	Promoting educational and training programs, fostering collaboration between academia, industry, and government stakeholders.

By addressing these challenges and promoting collaboration among stakeholders, the smart building industry can continue to evolve and contribute to the creation of more efficient, sustainable, and user-friendly built environments.

Future Trends and Developments

As the smart building industry continues to evolve, the role of IoT in shaping the future of civil engineering and construction will become increasingly significant. In this section, we will explore the future of smart buildings and discuss emerging technologies and research directions that may influence the evolution of these environments.

Artificial Intelligence (AI): The integration of AI and machine learning techniques into smart building systems offers significant potential for enhancing building performance, energy efficiency, and user experience (Farzaneh, H., Malehmirchegini, L., Bejan, A., Afolabi, T., Mulumba, A., & Daka, P. P., 2021). AI algorithms can analyze data collected from IoT devices to optimize building operations, predict equipment failures, and identify patterns in energy consumption. As AI capabilities continue to advance, we can expect increased adoption of AI-driven solutions in smart buildings, leading to more efficient and intelligent environments (Bakri Hassan, M., Sayed Ali Ahmed, E., & Saeed, R. A, 2021).

Data Analytics: The vast amount of data generated by IoT devices in smart buildings can be leveraged for deeper insights into building operations and occupant behavior (Hildayanti, A., & Machrizzandi, M. S., 2020). To find trends, spot abnormalities, and improve building performance, advanced data analytics techniques like big data processing and predictive analytics can be used. As data analytics technologies advance, we can anticipate them to play a bigger part in guiding decision-making and advancing smart building technology.

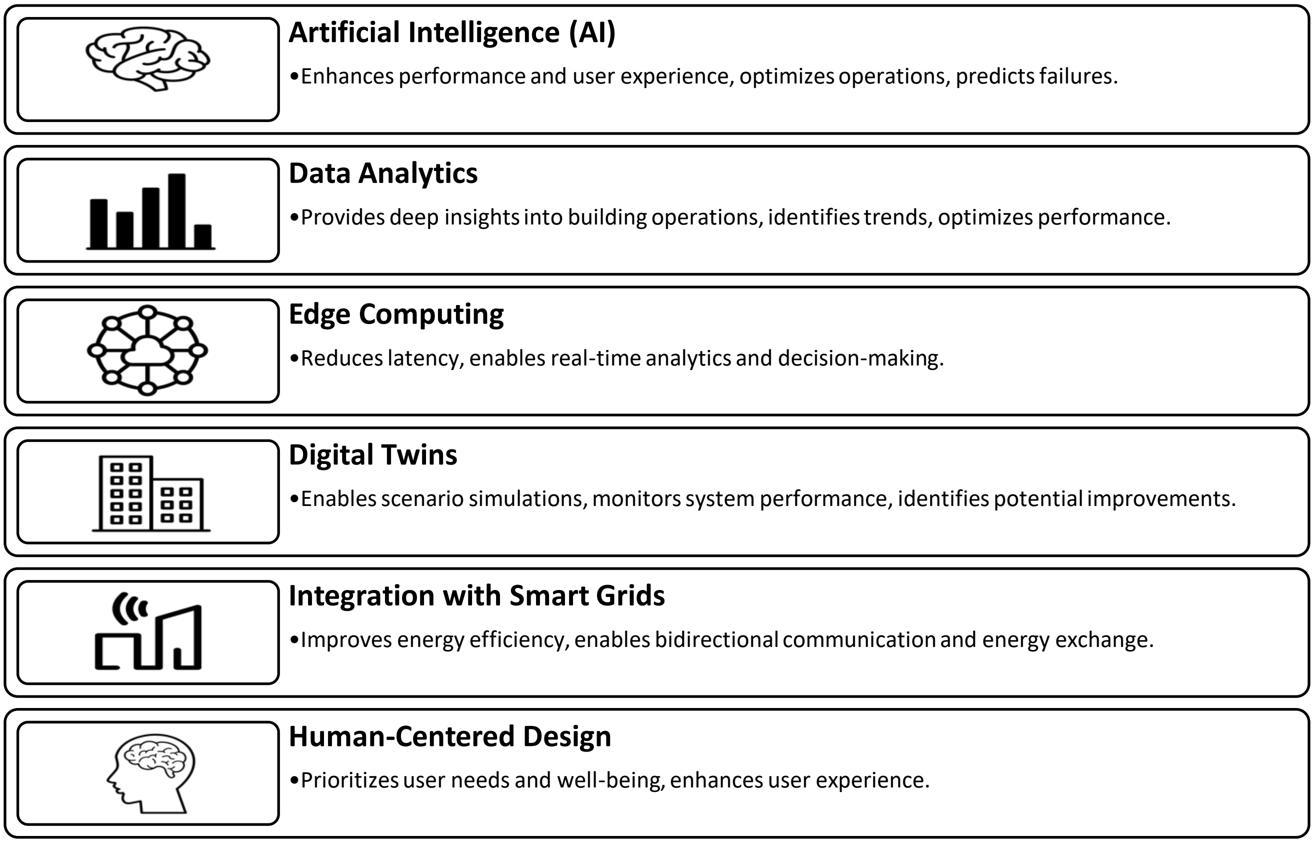
Edge Computing: As IoT devices proliferate in smart buildings, there is a rising need for processing power to handle and analyze data at the network edge (Shah, S. F. A., Iqbal, M., Aziz, Z., Rana, T. A., Khalid, A., Cheah, Y.-N., & Arif, M., 2022). Edge computing can help address this challenge by performing data processing tasks closer to the data source, reducing latency, and minimizing the reliance on centralized cloud resources. The integration of edge computing in smart buildings can enable real-time analytics and decision-making, contributing to more responsive and adaptive environments.

Digital Twins: A potent technique for maximizing the efficiency of smart buildings is the development of digital twins, which are virtual replicas of physical assets or systems (Tao, F., Cheng, J., Qi, Q., Zhang, M., Zhang, H., & Sui, F., 2018). By creating a digital replica of a building, facility managers can simulate various scenarios, monitor the performance of building systems, and identify potential areas for improvement. As digital twin technology continues to advance, we can expect to see increased adoption of this approach in smart building management and operations.

Integration with Smart Grids: The future of smart buildings will likely involve increased integration with smart grid systems, enabling bidirectional communication and energy exchange between buildings and the grid (Thomas, M. L., Marie-Claude, B., Lieve, H., Gregor, H., Javad, M., Doug, N., Dieter, P., Shanti, P., & Richard, T. W., 2016). This integration can lead to improved energy efficiency, demand-side management, and increased adoption of renewable energy sources. As smart grids and smart buildings become more interconnected, there will be new opportunities for innovation and collaboration in the energy sector.

Human-Centered Design: As the focus on user experience in smart buildings continues to grow, we can expect to see increased attention on human-centered design principles (Alessandra, L. N., & Mauro, O., 2018). This approach prioritizes the needs, preferences, and well-being of building occupants, ensuring that smart building technologies are developed with the end-user in mind. Future smart building developments may incorporate biophilic design elements, improved indoor environmental quality, and more personalized control systems to create spaces that promote occupant health and well-being.

Figure 2: Future Trends and Developments in Smart Buildings



In conclusion, the development of new technologies and research areas, such as artificial intelligence (AI), data analytics, edge computing, digital twins, smart grid integration, and human-centered design, will have a significant impact on the future of smart buildings. As the industry continues to evolve, we can expect to see smart buildings becoming more intelligent, efficient, and user-friendly, offering significant potential for transforming the built environment and the way we live and work.

Conclusion

In this study, the authors explored the intersection of civil engineering and the Internet of Things (IoT) within the context of smart buildings. The use of IoT technology, such as sensors, actuators, and communication protocols, was discussed, underscoring their essential roles in energy management, automation, and security. The multitude of benefits offered by smart buildings, particularly in terms of energy efficiency, sustainability, and enhanced user experience, were examined.

This research also shed light on the complexities associated with the integration of IoT technology into smart buildings, including interoperability issues and security and privacy concerns. Despite these challenges, the research also highlighted the ample opportunities for innovation and enhancement in this rapidly growing field. In contemplating the future trajectory of smart buildings, the discussion extended to emerging technologies and methodologies, including artificial intelligence (AI), data analytics, edge computing, digital twins, and human-centered design.

The integration of IoT technology into smart buildings offers an exceptional opportunity to reshape the built environment towards an energy-efficient future. However, to effectively tackle the challenges and fully harness the potential of this rapidly evolving field, continuous research, collaboration, and innovation are integral. Emphasizing the role of civil engineering in the development of energy-efficient infrastructure, this study contributes to the body of literature focusing on IoT-driven smart buildings. The insights garnered serve as a guide for future research and innovations, steering us towards a future with smart buildings that are not only intelligent and user-friendly, but also increasingly energy-efficient and sustainable.

Future Studies

The development of more reliable and scalable IoT solutions that handle the issues of interoperability, security, and privacy may be the main topic of future study in the fields of smart buildings and civil engineering. Additionally, to further improve building performance and occupant well-being, researchers might look into novel integration strategies for cutting-edge technologies like edge computing, AI, and data analytics. Other potential directions for future research include examining the contribution of human-centered design to the creation of smart building technologies and the effects of biophilic design components on occupant productivity and health.

Declarations

Ethical Approval

Not applicable. This manuscript does not involve any human and/or animal studies.

Competing Interests

The authors declare that they have no competing interests of a financial or personal nature that could have influenced the work reported in this manuscript.

Authors' Contributions

Arkar Htet 1* and Theingi Aung 3 were the main contributors to the writing of the manuscript. Dr.Sui Reng Liana 2 and Dr. Amiya Bhaumik 4 supervised the manuscript. All authors reviewed the manuscript and gave their approval for the final version to be published. All authors agree to be accountable for all aspects of the work and will ensure that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

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Availability of Data and Materials

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RESEARCH ARTICLE

Artificial Intelligence and Machine Learning for Real-time Energy Demand Response and Load Management

Abdulgaffar Muhammad[1*], Aisha Ahmad Ishaq[2], Igbinovia Osaretin B[3], Mohammed Bello Idris[4]

[1]Department of Business Administration, Ahmadu Bello University, Nigeria
[2]Department of Business Administration, Kano State Polytechnic Nigeria
[3]Nile University, Nigeria
[4]Department of Business Administration, Kaduna State University, Nigeria

Corresponding Author: Abdulgaffar Muhammad: muhammadabdulgaffar306@gmail.com
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Abstract

Within this compendium, an exhaustive examination is undertaken to scrutinize the intricate amalgamation of artificial intelligence (AI) and machine learning (ML) techniques within the paradigm of real-time energy demand response and load management. Placing paramount importance on the pervasive significance of AI and ML, this research expounds upon their profound capabilities to adroitly harmonize the delicate interplay between supply and demand, meticulously calibrate the multifarious dimensions of grid stability, and optimize the boundless potential inherent in renewable energy resources. An in-depth analysis ensues, encompassing the deployment of AI algorithms, poised at the vanguard of demand response optimization, and the judicious utilization of ML techniques, flawlessly calibrated to deliver unerring accuracy across varying temporal scales in the realm of load forecasting. Furthermore, the seamless integration of AI into the very fabric of intelligent appliances and Internet of Things (IoT)-enabled systems unfolds, illuminating the path towards energy consumption optimization, ascertaining an intricate tapestry of interconnected devices, and engendering an ecosystem of intelligent load management. Notably, this comprehensive exposition delves into the far-reaching implications for optimal load management and resource allocation, magnifying the transformative potential that AI-driven algorithms hold in precisely balancing energy utilization and deftly managing the intricate interdependencies that permeate load distribution. Through meticulous elucidation, this illuminating manuscript emboldens the reader with insights into the progressive advancements and myriad benefits that the tandem of AI and ML confers upon the dynamic energy sector, charting an unyielding course towards unprecedented resilience and sustainable utilization of our cherished renewable energy resources.

Keywords: Artificial intelligence; Machine learning; Real-time energy demand response; Load management; energy consumption optimization; Renewable energy resources

Introduction

Real-time energy demand response and load management represent critical aspects of modern energy systems, necessitating a comprehensive understanding of the intricate dynamics and challenges involved. In an era marked by increasing energy consumption, diverse energy sources, and the integration of renewable energy, effective demand response and load management strategies have become imperative to ensure the stability, reliability, and efficiency of energy grids.

The concept of real-time energy demand response refers to the ability to dynamically adjust energy consumption in response to changes in supply and demand conditions. This flexibility enables energy consumers, such as residential, commercial, or industrial entities, to modify their electricity usage patterns to align with grid requirements. By actively participating in demand response programs, consumers can contribute to grid stability, reduce peak demand, and even lower energy costs.

Simultaneously, load management focuses on optimizing the allocation and utilization of available energy resources to meet the varying demands of consumers in an efficient manner. It involves the intelligent scheduling and control of energy loads, considering factors like time-of-use tariffs, energy storage systems, and the integration of distributed energy resources. The goal is to minimize wastage, reduce grid congestion, and achieve an optimal balance between energy supply and demand.

However, the complex nature of energy grids, characterized by intermittent renewable energy sources, diverse consumer behavior patterns, and the need for rapid decision-making, poses significant challenges to real-time demand response and load management. Traditional approaches often fall short in adapting to dynamic energy scenarios and fail to exploit the full potential of available resources.

Therefore, leveraging advanced technologies such as artificial intelligence (AI) and machine learning (ML) has emerged as a promising solution to address these challenges. AI, encompassing various computational techniques, empowers energy systems to intelligently analyze vast volumes of real-time data, identify patterns, and make informed decisions in real-time. ML, a subset of AI, enables energy systems to learn from historical data and make predictions or optimize control strategies.

By integrating AI and ML techniques into real-time energy demand response and load management systems, stakeholders can unlock numerous benefits. These technologies enable precise demand forecasting, considering factors like weather conditions, consumer behavior, and historical patterns, thereby facilitating proactive load management strategies. Furthermore, AI and ML algorithms can adapt to dynamic energy scenarios, continuously learning and optimizing energy consumption patterns to enhance grid stability and reliability.

In conclusion, real-time energy demand response and load management represent crucial facets of contemporary energy systems. The integration of AI and ML technologies offers a transformative approach to address the complexities and optimize the efficiency of these systems. By leveraging advanced computational techniques and data analytics, stakeholders can revolutionize demand response strategies, facilitate precise load forecasting, and ensure effective utilization of available energy resources.

Significance of artificial intelligence (AI) and machine learning (ML) in optimizing energy consumption

The significance of artificial intelligence (AI) and machine learning (ML) in optimizing energy consumption cannot be overstated, as these advanced technologies possess immense potential to revolutionize the energy sector by enabling intelligent decision-making, enhancing efficiency, and maximizing the utilization of available resources.

AI, a branch of computer science, encompasses a range of techniques and algorithms that allow energy systems to analyze complex data patterns, recognize trends, and make data-driven predictions. By leveraging AI, energy consumption patterns can be precisely analyzed, enabling the identification of opportunities for optimization and improvement.

Furthermore, ML, a subset of AI, empowers energy systems to learn from historical data, adapt to changing circumstances, and make autonomous decisions based on experience. ML algorithms can automatically identify patterns, relationships, and anomalies in large datasets, enabling the discovery of insights that would be challenging or time-consuming for humans to discern.

When applied to energy consumption optimization, AI and ML technologies offer multifaceted benefits. Firstly, these technologies facilitate accurate and granular energy demand forecasting. By analyzing diverse factors such as weather conditions, historical consumption data, and behavioral patterns, AI and ML algorithms can generate forecasts that align with the unique requirements of specific regions, timeframes, or consumer segments. This enhanced forecasting capability enables energy providers to plan and allocate resources effectively, minimizing waste and avoiding under or overutilization of energy sources.

Moreover, AI and ML enable real-time monitoring and control of energy consumption. By integrating intelligent sensors and IoT-enabled devices, energy systems can gather vast amounts of data related to energy usage patterns, environmental conditions, and grid stability. AI algorithms can then process this data in real-time, providing actionable insights for optimizing energy consumption. For instance, AI-based systems can automatically adjust energy loads, prioritize energy distribution based on demand, and identify potential inefficiencies or anomalies that require immediate attention.

Additionally, AI and ML techniques can facilitate the seamless integration of renewable energy sources into the grid. As renewable energy generation exhibits inherent variability due to weather conditions and other factors, AI algorithms can forecast renewable energy generation patterns and align them with energy demand, optimizing the use of clean energy sources and reducing reliance on fossil fuels. ML algorithms can also contribute to the development of advanced control strategies for managing distributed energy resources, such as solar panels or wind turbines, by dynamically adjusting their output based on real-time energy demand.

Furthermore, AI and ML can enhance energy efficiency through adaptive learning and optimization algorithms. By continuously analyzing data and learning from system performance, AI-based energy systems can automatically optimize energy usage, identifying opportunities for load shifting, demand response, or energy storage utilization. These optimization strategies, driven by AI and ML, lead to improved grid stability, reduced energy costs, and minimized environmental impact.

In conclusion, the significance of AI and ML in optimizing energy consumption is profound and far-reaching. These advanced technologies enable precise demand forecasting, real-time monitoring and control, seamless integration of renewable energy sources, and adaptive learning for energy efficiency. By harnessing the power of AI and ML, energy systems can unlock new levels of efficiency, sustainability, and resilience, paving the way for a greener and more intelligent energy future.

AI-Enabled Demand Response Algorithms

Analysis of real-time energy data and consumer behavior patterns

Analysis of real-time energy data and consumer behavior patterns plays a pivotal role in understanding energy consumption patterns, identifying trends, and developing effective strategies for optimizing energy management. By analyzing real-time energy data and consumer behavior, valuable insights can be gleaned, leading to informed decision-making and targeted interventions that can positively impact energy efficiency and sustainability.

One crucial aspect of real-time energy data analysis is the utilization of advanced data analytics techniques, such as machine learning (ML) algorithms. ML algorithms can process large volumes of energy data, uncover hidden patterns, and generate predictions or recommendations based on historical and real-time data inputs. For example, ML algorithms can analyze energy consumption patterns across different time periods, identify peak demand periods, and suggest load management strategies to reduce energy consumption during those periods (Siano, 2014). These algorithms can also detect anomalies in energy data, such as sudden spikes or drops in consumption, which may indicate equipment malfunctions or inefficient energy usage (Tautz-Weinert et al., 2020).

Moreover, the analysis of consumer behavior patterns is essential for understanding energy consumption habits and developing tailored interventions to promote energy efficiency. Real-time energy data combined with consumer behavioral data can provide insights into factors influencing energy usage, such as time of day, occupancy patterns, or device usage. For instance, studies have shown that energy consumption patterns can vary significantly based on factors such as weather conditions, demographic profiles, and household characteristics (Wang et al., 2020). By analyzing these patterns, energy providers and policymakers can design targeted energy efficiency programs, educate consumers about their energy usage patterns, and promote behavioral changes that lead to reduced energy consumption (Liao et al., 2018).

Furthermore, the advent of smart meters and advanced metering infrastructure (AMI) has facilitated the collection of high-resolution energy data, enabling more detailed analysis of energy consumption patterns. Smart meters provide real-time energy usage data at frequent intervals, allowing for the identification of short-term fluctuations and load profiles. This granular data, when combined with consumer behavior data, can help identify energy-saving opportunities, assess the impact of energy efficiency initiatives, and develop personalized energy management strategies for consumers (Jin et al., 2017).

In conclusion, the analysis of real-time energy data and consumer behavior patterns is crucial for optimizing energy management and promoting energy efficiency. By leveraging advanced data analytics techniques, such as ML algorithms, and integrating consumer behavior data, energy providers and policymakers can gain valuable insights into energy consumption patterns, detect anomalies, and design targeted interventions. The utilization of real-time energy data analysis in conjunction with consumer behavior analysis enables the development of tailored energy management strategies that can contribute to a more sustainable and efficient energy future.

Development and application of AI algorithms for demand response optimization

The development and application of AI algorithms for demand response optimization have emerged as a promising approach to effectively manage and balance energy supply and demand in real-time. By leveraging the capabilities of AI, energy systems can dynamically respond to fluctuating energy conditions and consumer demand patterns, leading to enhanced grid stability and optimized energy utilization.

One notable AI algorithm that has gained traction in demand response optimization is reinforcement learning (RL). RL algorithms, such as Q-learning, enable an AI agent to learn optimal decision-making policies through interaction with the environment. In the context of demand response, RL algorithms can be employed to learn and adapt to changing energy conditions and consumer behavior, identifying the most effective strategies to optimize energy consumption and demand response actions (Vrba et al., 2018).

Deep learning algorithms, particularly deep neural networks (DNNs), have also demonstrated their efficacy in demand response optimization. DNNs can process vast amounts of energy data, capturing intricate patterns and relationships, to make accurate predictions and inform demand response decisions. For instance, DNNs can analyze historical energy consumption data, weather conditions, and grid information to forecast energy demand and support decision-making regarding load shedding or shifting strategies (Li et al., 2021).

Ensemble learning techniques have shown promise in demand response optimization as well. Ensemble algorithms combine multiple models to improve prediction accuracy and robustness. By leveraging the diversity of multiple models, ensemble learning can enhance the reliability of demand response predictions and aid in developing more effective strategies for load management and energy utilization (Gupta et al., 2020).

Furthermore, genetic algorithms (GAs) have been applied to demand response optimization. GAs employ an evolutionary approach to search for optimal solutions within a large search space. These algorithms mimic the process of natural selection, evolving and refining solutions over multiple iterations. In the context of demand response, GAs can be used to optimize energy scheduling, resource allocation, and load balancing, enabling efficient energy consumption while considering various constraints and objectives (Wang et al., 2018).

The development and application of AI algorithms for demand response optimization have demonstrated promising results, offering significant benefits in terms of grid stability, energy efficiency, and cost savings. By leveraging RL, deep learning, ensemble learning, and genetic algorithms, energy systems can effectively respond to dynamic energy conditions, predict demand patterns accurately, and optimize energy consumption strategies to achieve efficient demand response actions.

Machine Learning for Load Forecasting

ML techniques for accurate load forecasting at different time scales

ML techniques have proven to be valuable tools for accurate load forecasting at different time scales, enabling energy systems to anticipate and plan for future energy demand. By analyzing historical load data and incorporating relevant factors, such as weather conditions, holidays, and economic indicators, ML algorithms can provide accurate load forecasts that assist in efficient energy scheduling, resource allocation, and grid planning.

One commonly utilized ML technique for load forecasting is the implementation of neural networks. Neural networks, particularly long short-term memory (LSTM) networks, have demonstrated their effectiveness in capturing temporal dependencies and complex patterns in load data. These networks can model nonlinear relationships and learn from historical load data to make accurate predictions for future load demand (Chen et al., 2019). By training LSTM models on historical load data and associated variables, such as temperature and time of day, accurate load forecasts can be generated at various time scales, from short-term to long-term predictions.

Support vector machines (SVMs) have also been applied for load forecasting with notable success. SVMs utilize statistical learning theory to find optimal hyperplanes that separate and classify data points. In load forecasting, SVMs can be trained on historical load data, along with relevant input features, to create models that accurately predict future load demand (Nguyen et al., 2019). By considering historical load patterns and associated variables, SVM-based load forecasting models can capture the inherent complexities of energy consumption patterns and generate accurate load forecasts.

Another ML technique used for load forecasting is the implementation of random forests. Random forests are ensemble learning methods that combine multiple decision trees to make predictions. In load forecasting, random forests can be trained on historical load data, weather information, and other relevant variables to develop models that capture the interplay between various factors affecting energy demand (Nguyen et al., 2019). The ensemble nature of random forests allows for robust predictions, mitigating the impact of outliers and noise in the data.

Additionally, gradient boosting algorithms, such as XGBoost and LightGBM, have gained popularity in load forecasting applications. These algorithms build an ensemble of weak predictive models to create a strong predictive model. By iteratively optimizing the model's performance, gradient boosting algorithms can capture intricate relationships and nonlinearities in load data, resulting in accurate load forecasts (Raza et al., 2020).

The application of ML techniques for load forecasting offers significant benefits in energy management and planning. Accurate load forecasts enable energy providers to optimize resource allocation, ensure grid stability, and avoid unnecessary costs associated with under or overutilization of energy resources. By leveraging neural networks, support vector machines, random forests, and gradient boosting algorithms, energy systems can make informed decisions based on accurate load predictions, contributing to efficient load management and enhanced grid reliability.

Implications for efficient load management and resource allocation

Efficient load management and resource allocation are critical aspects of energy systems that directly impact grid stability, cost-effectiveness, and sustainability. The use of ML techniques for load forecasting offers significant implications for optimizing load management and resource allocation processes, leading to more efficient utilization of energy resources.

Accurate load forecasting provided by ML techniques enables energy providers to effectively plan and allocate resources based on anticipated energy demand. By accurately predicting load patterns at different time scales, energy systems can allocate resources, such as generation capacity, energy storage, and grid infrastructure, more efficiently. This proactive approach ensures that sufficient resources are available to meet demand, reducing the risk of under or overutilization and minimizing the need for costly last-minute adjustments (Yuan et al., 2019). Efficient resource allocation based on accurate load forecasts also contributes to optimal energy utilization, as energy systems can balance supply and demand, reduce energy waste, and optimize the overall efficiency of the grid.

Furthermore, ML-based load forecasting allows for more effective demand response programs. Demand response initiatives aim to adjust energy consumption patterns to align with grid conditions and optimize the utilization of energy resources. Accurate load forecasts enable energy providers to identify peak demand periods, incentivize load shifting or shedding, and encourage consumer participation in demand response programs (Nguyen et al., 2019). By leveraging ML techniques for load forecasting, energy systems can develop targeted demand response strategies, leading to more efficient load management and reduced strain on the grid during high-demand periods.

The implications of ML-based load forecasting also extend to renewable energy integration and grid stability. The integration of renewable energy sources, such as solar and wind, introduces variability and uncertainty into the grid due to their intermittent nature. Accurate load forecasts allow energy systems to anticipate renewable energy generation and plan for its integration more effectively. ML techniques can analyze historical data on renewable energy generation and weather conditions to predict future renewable energy availability, helping grid operators optimize the utilization of renewable energy resources and minimize reliance on traditional fossil fuel-based generation (Zhang et al., 2021). By aligning load management strategies with renewable energy availability, energy systems can achieve a more sustainable and resilient grid.

In conclusion, the utilization of ML techniques for load forecasting has significant implications for efficient load management and resource allocation. Accurate load forecasts enable energy providers to optimize resource allocation, plan for demand response actions, and integrate renewable energy sources effectively. By leveraging ML algorithms and incorporating real-time data, energy systems can enhance grid stability, reduce operational costs, and promote sustainable energy utilization.

AI-Driven Smart Appliances and Devices

Integration of AI into smart appliances and IoT-enabled systems

The integration of AI into smart appliances and IoT-enabled systems has revolutionized load management and energy consumption optimization. By leveraging AI algorithms, these intelligent systems can analyze and interpret data from various sensors, devices, and energy sources to make informed decisions and optimize energy consumption patterns.

One of the key AI algorithms used in the integration of smart appliances and IoT-enabled systems is reinforcement learning (RL). RL algorithms, such as Q-learning, enable appliances and devices to learn and adapt to their environment by taking actions and receiving feedback or rewards. In the context of energy optimization, RL algorithms can be applied to smart appliances to learn optimal energy consumption strategies based on real-time data and user preferences (Kaur et al., 2021). By continuously interacting with the environment and receiving feedback, AI-enabled appliances can dynamically adjust their energy usage, leading to more efficient load management.

Another algorithm commonly used in the integration of AI and IoT-enabled systems is deep learning, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs). These algorithms excel at processing large amounts of data and extracting meaningful patterns. In the context of smart appliances and IoT-enabled systems, deep learning algorithms can analyze sensor data, energy consumption patterns, and environmental factors to optimize energy usage (Wu et al., 2019). CNNs can analyze visual data from cameras or image sensors to identify energy-intensive activities, while RNNs can capture temporal dependencies in energy consumption data to predict future energy needs and adjust appliance settings accordingly.

Additionally, AI algorithms such as clustering algorithms, genetic algorithms, and swarm intelligence algorithms can be applied to smart appliances and IoT-enabled systems for load management and energy optimization. Clustering algorithms, such as k-means clustering, can group appliances based on similar usage patterns and optimize their collective energy consumption (Gao et al., 2019). Genetic algorithms can be employed to optimize appliance scheduling and energy usage by evolving and refining schedules over multiple iterations (Choi et al., 2020). Swarm intelligence algorithms, inspired by collective behaviors of social insects, can enable appliances and devices to coordinate their energy usage and adapt to dynamic energy conditions in a distributed manner (Yang et al., 2021).

These complex algorithms are represented by mathematical equations that describe their behavior and learning processes. For example, the Q-learning algorithm in reinforcement learning utilizes the following equation to update the action-value function (Q-value) based on the observed rewards and the estimated value of the next state-action pair:

$$\mathbf{Q(s, a) = Q(s, a) + \alpha\ [r + \gamma\ max(Q(s', a')) - Q(s, a)]}$$

Where Q(s, a) represents the Q-value for state-action pair (s, a), r is the observed reward, s' is the next state, a' is the next action, α is the learning rate, and γ is the discount factor.

In summary, the integration of AI into smart appliances and IoT-enabled systems harnesses the power of complex algorithms such as reinforcement learning, deep learning, clustering algorithms, genetic algorithms, and swarm intelligence algorithms. These algorithms enable appliances and devices to optimize energy consumption patterns based on real-time data, user preferences, and environmental factors, ultimately leading to more efficient load management and energy utilization.

Optimizing energy consumption and enabling intelligent load management

Optimizing energy consumption and enabling intelligent load management are critical objectives in modern energy systems. The integration of AI algorithms and advanced techniques facilitates the achievement of these goals by leveraging data-driven approaches to analyze energy patterns, make informed decisions, and optimize energy consumption in real-time.

One powerful algorithm used for optimizing energy consumption and load management is the Genetic Algorithm (GA). GA is a computational technique inspired by the principles of natural selection and evolution. It can be applied to solve complex optimization problems, including energy management. GA operates by evolving a population of potential solutions, iteratively improving them through selection, crossover, and mutation processes (Kennedy & Eberhart, 1995). In the context of energy consumption optimization, GA can be employed to find optimal schedules for appliances, considering factors such as energy cost, user preferences, and demand response requirements (Huang et al., 2020). By exploring different combinations of appliance operation schedules, GA can identify energy-efficient configurations that minimize overall energy consumption and maximize load balancing.

Another algorithm used for intelligent load management is the Ant Colony Optimization (ACO) algorithm. ACO is inspired by the foraging behavior of ants and has been successfully applied to various optimization problems. In load management, ACO can be utilized to optimize the scheduling and coordination of appliances and devices. By simulating the pheromone trail laying and following behavior of ants, ACO can guide the allocation of energy resources and determine the best load balancing strategies (Chong et al., 2018). ACO algorithms can dynamically adapt to changes in energy demand, load conditions, and user preferences, providing flexible and efficient load management solutions.

Furthermore, Machine Learning algorithms, such as Support Vector Machines (SVM) and Random Forests (RF), can contribute to optimizing energy consumption and enabling intelligent load management. SVM is a supervised learning algorithm that utilizes a decision boundary to classify data points. In the context of load management, SVM can analyze historical energy consumption data, along with other variables such as weather conditions and occupancy patterns, to predict future load demand (Nguyen et al., 2019). These predictions can be used to optimize energy scheduling, allocate resources, and minimize peak demand.

Random Forests, on the other hand, are ensemble learning methods that combine multiple decision trees to make predictions. In the context of load management, Random Forests can leverage historical energy consumption patterns, weather data, and other relevant variables to generate accurate load forecasts (Raza et al., 2020). By considering the interplay of various factors affecting energy consumption, Random Forests can provide insights for intelligent load management decisions, such as load shifting or shedding strategies.

These algorithms, along with others like Particle Swarm Optimization (PSO) and Reinforcement Learning (RL), empower energy systems to optimize energy consumption and enable intelligent load management. By leveraging GA, ACO, SVM, Random Forests, and other algorithms, energy systems can make data-driven decisions, adapt to changing conditions, and achieve efficient energy utilization while maintaining grid stability.

Predictive Maintenance and Fault Detection using ML

ML algorithms for predictive maintenance of energy assets

Predictive maintenance plays a crucial role in ensuring the optimal performance and reliability of energy assets. Machine Learning (ML) algorithms offer valuable tools for analyzing historical data, sensor readings, and anomaly detection techniques to predict and prevent potential faults in energy assets. In this section, we will discuss two prominent ML algorithms for predictive maintenance: Recurrent Neural Networks (RNNs) and Support Vector Machines (SVMs).

Recurrent Neural Networks (RNNs) are widely used in predictive maintenance due to their ability to capture temporal dependencies in sequential data. RNNs are particularly effective in processing time-series sensor data collected from energy assets. The key equation governing the behavior of RNNs is the recurrent hidden state equation, which calculates the hidden state vector at each time step based on the current input and the previous hidden state:

$$h(t) = f(Wx(t) + Uh(t-1) + b)$$

where h(t) represents the hidden state at time t, x(t) is the input at time t, W and U are weight matrices, b is the bias vector, and f is the activation function (e.g., sigmoid or tanh).

Long Short-Term Memory (LSTM) networks, a type of RNN, have shown promising results in predictive maintenance tasks. LSTM models address the vanishing gradient problem of traditional RNNs, allowing them to effectively capture long-term dependencies. The LSTM equations consist of multiple gating mechanisms, which control the flow of information within the network. The equations governing the behavior of LSTM units are as follows:

$$i(t) = \sigma(Wi\, x(t) + Ui\, h(t-1) + bi)\; f(t) = \sigma(Wf\, x(t) + Uf\, h(t-1) + bf)\; o(t) = \sigma(Wo\, x(t) + Uo\, h(t-1) + bo)\; g(t) = \tanh(Wg\, x(t) + Ug\, h(t-1) + bg)\; c(t) = f(t) \odot c(t-1) + i(t) \odot g(t)\; h(t) = o(t) \odot \tanh(c(t))$$

where i(t), f(t), o(t), and g(t) are the input, forget, output, and candidate cell vectors at time t, respectively. The matrices Wi, Ui, Wf, Uf, Wo, Uo, Wg, Ug, and biases bi, bf, bo, bg are the learnable parameters of the LSTM.

Support Vector Machines (SVMs) are another powerful ML algorithm used in predictive maintenance of energy assets. SVMs are supervised learning models that can be trained on historical data to classify normal and abnormal asset conditions. The key equation in SVM is the decision function, which determines the class label of a new sample based on its feature vector x:

$$f(x) = \text{sign}(\Sigma\ \alpha i\ yi\ K(x, xi) + b)$$

where f(x) is the predicted class label, αi are the Lagrange multipliers obtained during the training process, yi is the corresponding class label, K(x, xi) is the kernel function that measures the similarity between the input sample x and the support vectors xi, and b is the bias term.

SVMs utilize a decision boundary to separate different classes, enabling the detection of anomalies and potential faults in energy assets. By leveraging historical data and extracting relevant features, SVM models can provide early warnings of potential failures, allowing for proactive maintenance actions.

In summary, Recurrent Neural Networks (RNNs) and Support Vector Machines (SVMs) are powerful ML algorithms used in predictive maintenance of energy assets. RNNs, with their ability to capture temporal dependencies, are well-suited for analyzing time-series sensor data. SVMs, on the other hand, excel in handling high-dimensional feature spaces and binary classification tasks. Therefore, in the context of predictive maintenance of energy assets, SVMs are particularly effective in identifying anomalies and classifying fault conditions based on various sensor inputs. By leveraging the strengths of both RNNs and SVMs, a comprehensive and accurate predictive maintenance system can be established to enhance asset reliability and minimize downtime

Identification of potential faults and optimization of maintenance schedules

Identification of potential faults and optimization of maintenance schedules are critical aspects of predictive maintenance for energy assets. By leveraging advanced algorithms and techniques, it becomes possible to detect early signs of faults and plan maintenance activities more efficiently, minimizing downtime and maximizing asset performance. In this section, we will explore the process of identifying potential faults and optimizing maintenance schedules using machine learning and optimization algorithms.

One key step in the identification of potential faults is the analysis of sensor data and the detection of anomalies. Machine learning algorithms, such as Autoencoders, are commonly used for this purpose. Autoencoders are neural networks that aim to reconstruct their input data, learning a compact representation of normal patterns in the process. When exposed to faulty or abnormal data, an Autoencoder will struggle to accurately reconstruct the input, indicating the presence of a potential fault (Luo et al., 2020). By monitoring the reconstruction error or utilizing anomaly detection techniques, potential faults can be identified, and maintenance actions can be initiated.

Once potential faults are detected, optimizing maintenance schedules becomes crucial to ensure efficient asset management. This task involves finding the optimal time to perform maintenance activities, considering factors such as asset criticality, resource availability, and operational constraints. Various optimization algorithms, such as Genetic Algorithms (GAs), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO), can be employed for this purpose.

Genetic Algorithms (GAs) are optimization algorithms inspired by natural evolution. GAs iteratively generate a population of potential solutions and apply evolutionary operations such as selection, crossover, and mutation to improve the solutions over time. In the context of maintenance scheduling, GAs can be utilized to find the best combination of maintenance tasks and their respective timing, aiming to minimize maintenance costs, maximize asset availability, and reduce the risk of failures (Liu et al., 2021). By encoding maintenance tasks as genes and evaluating their fitness based on predefined objectives, GAs can effectively optimize maintenance schedules.

Particle Swarm Optimization (PSO) is another optimization algorithm commonly used for maintenance scheduling. PSO mimics the behavior of a swarm of particles searching for the optimal solution in a problem space. Each particle represents a potential solution, and their movement is influenced by their own best position and the global best position discovered by the swarm. In the context of maintenance scheduling, PSO can be applied to find the optimal sequence and timing of maintenance tasks, considering constraints such as resource availability and operational requirements (Babu et al., 2021). By iteratively updating the particle positions based on their own and the swarm's best-known solutions, PSO converges towards an optimal maintenance schedule.

Ant Colony Optimization (ACO) is inspired by the foraging behavior of ants and has been successfully applied to various optimization problems. In maintenance scheduling, ACO can be utilized to find the best sequence and timing of maintenance tasks by simulating the pheromone trail laying and following behavior of ants. By assigning pheromone values to maintenance tasks and iteratively updating them based on their performance, ACO can guide the construction of optimal maintenance schedules (Tan et al., 2019). ACO algorithms adapt to changes in asset conditions and optimize maintenance schedules accordingly.

In conclusion, the identification of potential faults and optimization of maintenance schedules are crucial for effective predictive maintenance of energy assets. Machine learning algorithms, such as Autoencoders, help in detecting anomalies and identifying potential faults, while optimization algorithms like Genetic Algorithms, Particle Swarm Optimization, and Ant Colony Optimization aid in finding the optimal timing and sequencing of maintenance tasks. By leveraging these advanced techniques, energy asset managers can optimize maintenance strategies, enhance asset performance, and minimize operational disruptions.

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RESEARCH ARTICLE

Enhancing the performance of Gravitational Water Vortex Turbine through Novel Blade Shape by Flow Simulation Analysis

Aamer Sharif[1], Adnan Aslam Noon[2], Riaz Muhammad[3], Waqas Alam[1]

[1]Department of Mechanical Engineering CECOS University of Information Technology and Emerging Sciences, Peshawar, Pakistan (ORCID: 0000-0003-1571-8675), aamirsharif120@gmail.com, (ORCID: 0009-0009-8240-8731).
Email: waqasalam8138@gmail.com
[2]Department of Mechanical Engineering, International Islamic University, Islamabad, Pakistan (ORCID: 0000-0002-0986-1312). Email: adnan.aslam@iiu.edu.pk
[3]Mechanical Engineering Department, College of Engineering, University of Bahrain, Bahrain. (ORCID: 0000-0003-3490-6065), Email: rmuhammad@uob.edu.bh)

Corresponding author: Aamer Sharif: aamirsharif120@gmail.com
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Abstract
The demand for renewable energy is increasing in developing countries. Producing electricity from low-head micro-hydropower, especially using the gravitational water vortex method, attracts researchers worldwide. The present study investigates the detailed performance evaluation of single-stage Gravitational water vortex turbine assembled in a conical basin. A detailed numerical study has been conducted on five different runners' shapes. The three best runners were selected for experimentation based on the water pressure inserted on the blades. The effects of blade shape on the performance parameters of single-stage Gravitational water vortex turbine have been investigated, including rotational speed, brake torque, and mechanical efficiency. The results showed that the round-curved runner performed better at the various flow rate levels regarding rotational speed, brake torque, and mechanical efficiency. Moreover, round curved runners absorbed maximum torque, producing higher rotational speed and mechanical efficiency. The blades of the round curved runner give an efficiency of 48.02 %, while the blades of the conical J shape runner and helical runner give an efficiency of 42.17 % and 38.64 %, respectively.

Keywords: Renewable Energy, GWVT, CFD, Blade Shape, Efficiency

Introduction

Today, mini and micro hydro-turbines are economical and viable power generation solutions to resolve the energy crisis (Shoukat, Noon et al. , Ullah, Siddiqi et al. , Ullah and Sharif 2022). Nowadays, conventional turbines like Kaplan and Pelton turbines are gaining interest, but their heads are greater than 3 m. Moreover, they require higher flow rates for effective operation (Abbasi, Abbasi et al. 2011, Power, McNabola et al. 2016). An alternate option to generate electricity from the low head and flow rate sites is installing the Gravitational water vortex turbine (Sharif, Siddiqi et al. 2020). Since the head of Gravitational water vortex turbine is as low as 0.7 m to 3 m, it can be installed on the rivers, streams, and irrigation canals to generate electricity from 1 kW to 100 kW for a few houses (Sharif, Siddiqi et al. , Sharif, Tipu et al. , Dhakal, Nepal et al. 2016, Timilsina, Mulligan et al. 2018, Muhammad, Sharif et al. 2022). The effective area of the blades of the Gravitational water vortex turbine is greater than that of the conventional turbine (Saleem, Cheema et al. 2020, Shoukat, Noon et al. 2021). Hence, GWVT produced more power output than conventional turbines (Tipu, Arif et al. , Ullah, Cheema et al. 2019).

Literature Review

Several studies were performed to evaluate the performance of Gravitational water vortex turbine. A numerical simulation was used to analyze the stable and optimum vortex pool formation of a Gravitational water vortex turbine (Shabara, Yaakob et al. 2015). The strength and the formation of the vortex in a conical basin have been analyzed numerically by changing the design parameters such as cone angle, basin height, basin inlet, and outlet diameter, and notch angle at a constant inflow rate (Dhakal, Timilsina et al. 2014). It was found through the CFD tool ANSYS Fluent that a conical basin produced more output and efficiency as compared to a cylindrical basin on the same inlet and outlet conditions through a runner position placed at 65 %-75 % from the top of the basin (Dhakal, Timilsina et al. 2015). The volume of fluid (VOF) method is used in ANSYS CFX to absorbed unsteady-state multiphase flow to influence the shape of the free surface vortex with the runner present in the basin (Nishi and Inagaki 2017). The two-phase flow analysis was carried out on different basin parameters through a CFD tool for determining the best basin configuration for the Gravitational water vortex turbine (Khan, Cheema et al. 2018). It was analyzed that an angle of 19º between the blade and hub extracted more power output (Dhakal, Bajracharya et al. 2017). The blades are curved vertically (Chattha, Cheema et al. 2017, Kueh, Beh et al. 2017, Khan, Cheema et al. 2018) and a horizontal plane (Dhakal, Timilsina et al. 2015) to accelerate the turbine's efficiency. A curve blades have better efficiency than straight blades when the curves are added at the exit of the turbine blades (Kueh, Beh et al. 2017). The geometry of the blades of the centrifugal (Nishi and Inagaki 2017), Francis (Gheorghe-Marius, Tudor et al. 2013), and impulse paddle-type (Power, McNabola et al. 2016, Kueh, Beh et al. 2017) blades configuration is also designed to investigate the overall performance of Gravitational water vortex turbine. The overall performance of a Gravitational water vortex turbine is reduced when the number of blades is increased from 6 to 12 (Dhakal, Nakarmi et al. 2014); however, when the number of blades is increased from 2 to 4 efficiency of the Gravitational water vortex turbine improved (Power, McNabola et al. 2016).

Various efforts have been made to investigate different aspects of Gravitational water vortex turbine; nevertheless, a novel design of the runner shape must be developed to increase the overall performance of single-stage Gravitational water vortex turbine. The authors were encouraged to use comprehensive numerical and experimental studies to propose a novel blade shape for Gravitational water vortex turbine based on the abovementioned concerns. As a result, the aim of this research involves a complete numerical and experimental examination of several runner shapes of a single-stage Gravitational water vortex turbine designed in a conical basin.

Materials and Method

Conical basin and Gravitational water vortex turbine

A Gravitational water vortex turbine setup mainly consists of a stationary or outer domain (a basin), and another is a rotary or inner domain called (turbine). A stationary basin portion is a big conical or cylindrical cross-section tank that creates a gravitational water vortex. The inner rotary domain, known as the blade domain, comprises a turbine with many blades that allow the blades to rotate symmetrically without affecting the basin domain's stationary state. The turbine's rotary component comprises one or more stages of a runner. Each runner is made up of several blades. The current study considered a conical basin and single-stage novel turbine configuration.

Numerical Method and Implementation

Simulation of Blades

The simulation of Gravitational water vortex turbine is divided into two steps as shown in Figure 1. The first step is selecting a conical basin and the second step is selecting the best three runners for experimentation.

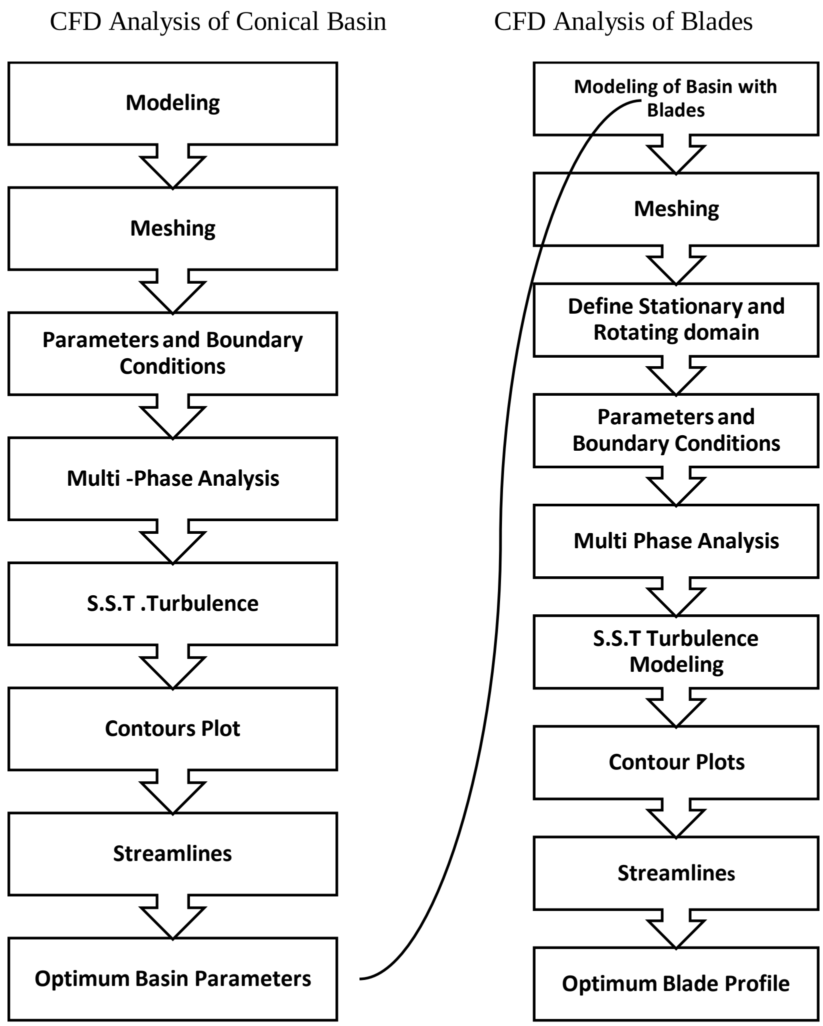

Figure 1: Simulation Methodology

The placement of the blades into the conical basin causes flow distortion. This water vortex distortion reduced tangential velocity while increasing radial and axial velocity. The vortex formation, height, and shape depend on the design of the blade. The current study analysis was implemented on several runners to obtain the best blade design for experimentation. Many factors play a role in the design of vortex turbines. One knows the pressure distribution on the turbine blades, which is essential in investigating the performance of turbine blades. The CFD study explores the water pressure pattern on the blades of Gravitational water vortex turbine. At a flow velocity of 0.1 m/s and a head of 0.61 m, the analysis was performed to affect water pressure on the turbine blades. Three different best-shape runners are selected through CFD analysis based on water pressure inserted on the blades. Figure 2 shows the maximum water pressure inserted on round curved blades. The energy of the water vortex was hit by the round curved runner and the conical J shape runner both horizontally and vertically. The runners are designed in such a way that maximal water hits the runner blades vertically and horizontally, ensuring that the vortex generated in a basin is not disrupted. The primary goal of the CFD study is to identify the optimal runner for Gravitational water vortex turbine that operates efficiently at various flow rates.

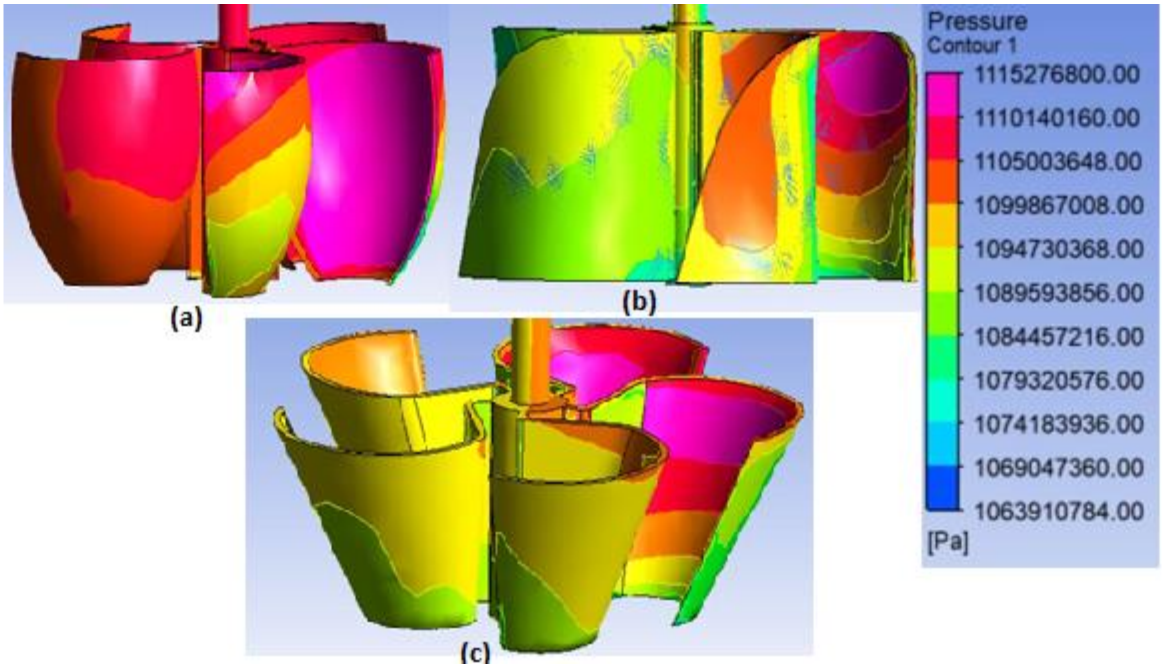

Figure 2. Water pressure inserted on (a) Round curved runner, (b) Helical runner (c) Conical J Shape runner

Selection of Blades

In twenty conceptual designs, ten best conceptual designs were modeled in solid work 18 for further simulation. Based on CFD analysis, the three best runners were selected and fabricated for experimental analysis.. Each runner has a different blade profile with round curved, helical and J shape conical configurations as shown in Figure 3. The current blades profiles are different from centrifugal, paddle and impulse type runners used in previous studies. The taper angle, impact angle, inlet, and outlet angle of each blade are different. The different three runner blades are designed to compel the vortex to give more power output. These blades can be easily manufactured to reduce the cost of casting and manufacturing. In the present study, 1 mm blades thicknesses have been modeled for numerical and manufactured for experimentation. Table 1 describes the dimension of each type of blade, respectively.

Table 1. Specification of the blade

Description	Symbol	Dimension
Blade length	l_b	85 mm
Blade height	h_b	67 mm
Hub height	h_h	70 mm
Hub radius	h_r	15 mm

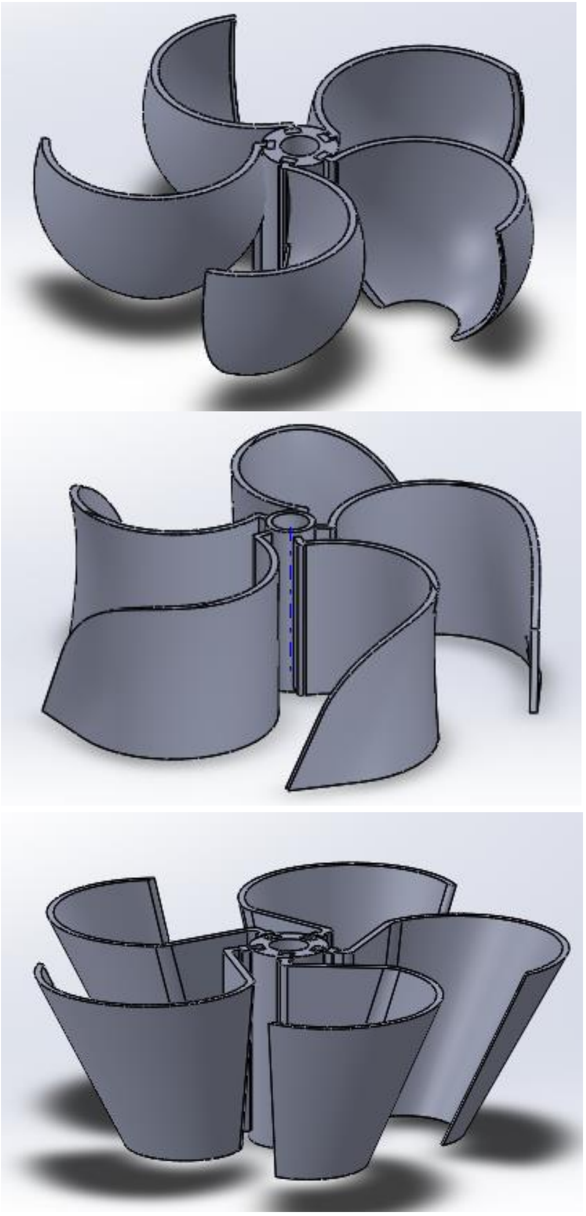

Figure 3. Modeling of the runners (a) round curved runner (b) helical runner (c) conical J shape runner

Experimental Set Up

The experimental setup of Gravitational water vortex turbine is divided into two-part, the static (conical basin and the upper channel) and the dynamic (turbine) part. The turbine setup has been assembled in a conical basin, with the runner having five blades. Mild steel of grade 1025 has been used to manufacture the upper stream and conical basin. . The experimental setup consists of a water storage tank (1000 L), a centrifugal pump (6hp), a conical basin, a Gravitational water vortex turbine assembly, and a supporting frame as shown in Figure 4. The supporting frame has the position of a step used for varying the water inlet head. The upper channel has a deflector directly connected to the top portion of the conical basin, which helps in water circulation and produces a strong vortex formation. Ball bearings supported the turbine's shaft to enhance the measurement of rpm and torque. The different level of water flow rates Q is measured with the help of a digital flow meter having an accuracy of ±0.02 %. The digital tachometer (Lutron DT-2236B, Accuracy ±0.05% + 1digit) measures the runner's rotational speed. The equations were references from past literature to measure the various input and output parameters (Khan, Cheema et al. 2018, Saleem, Cheema et al. 2020).

Figure 4. Experimental set up of Gravitational water vortex turbine

Results and discussions

Effect of blade shape on torque, rotational speed and mechanical efficiency

The torque increased as the water pressure on the runners increased (Sharif, Tipu et al.). As shown in Figure 5, the water flow rate level increases the brake force up to some level, but in the maximum water flow rate, the water pressure disturbs the runner blades, resulting in a reduction of torque. As torque is the product of moment arm and force, the greater resistance force applied on the runner produces greater torque. In three different runner shapes, the round curved runner shows maximum torque of 0.85 N-m, the conical J-shape runner absorbs median torque of 0.69 N-m, and the helical runner absorbs lesser torque of 0.61 N-m.

In the absence of no braking force applied on the runner shaft, all the runners showed maximum rotational speed. When force is applied on the shaft of the runners, the corresponding values of the rotational speed decrease (Sharif, Siddiqi et al.). Figure 6 shows that increasing the water flow rates from 0.004 m^3/s to 0.008 m^3/s increases the height of the water vortex, significantly increasing the runner's rotational speed. Water circulation increases due to increase in vortex height, the resultant formation of vortex vorticity. Vorticity measures the rotation of the fluid; therefore, increasing vorticity can increase the rotational speed (Ullah and Sharif 2022). Moreover, it can be absorbs that the maximum rpm of all three runners can be achieved under more significant vortex height. The water vortex height and water pressure decrease at 0.008 m^3/s, influencing the runner's rotational speed reduction. The decrease in rpm values in the graph shows no contact of the water vortex with the blades due to the small vortex height. As shown in Figure 6, the round curved runner showed maximum rotational speed of 141 rpm ; the conical J-shape runner absorbed 129 rpm, while helical runners showed lesser rotational speed of 121 rpm.

Three different runner-shapes, round curved, helical, and conical J-shape runners, have been developed to generate maximum efficiency. The mechanical efficiency is a ratio of brake shaft power to input hydraulic power (Ullah, Siddiqi et al.). The product of the applied torque and rotational speed both reflect the brake shaft power. Therefore, the efficiency of all the runners reflects the combined effects of applied torque and rotational speed as both the runner's applied torque and rotational speed perform better at an optimum level of water flow rates, producing maximum brake shaft power (Muhammad, Sharif et al. 2022). Therefore, the efficiency of all the runners performed best in the midrange level of water flow rates between the minimum and maximum levels. The round curved runner's value efficiencies have 37.06 %, 48.02 %, and 38.68 %, at 0.004 m^3/s, 0.006 m^3/s, and 0.008 m^3/s, respectively. This is because a round curved runner has been manufactured according to the vortex profile. Moreover, the mechanical efficiency of the round-curved runner is higher than the rest of the runners due to the area of contact of the blade configuration, with the water vortex being more than other runners. Hence, the blades of the round curve runner are preferred for power generation. The J shape runner (41.12 %) and helical runner showed the least efficiency of (37.55 %) compared to the round shape runner due to the low torque generated from these blades as shown in Figure 7. The low torque generated from these runners is due to the low extraction of energy from the vortex formation and caused a reduction in vortex height which absorbed the least efficiency.

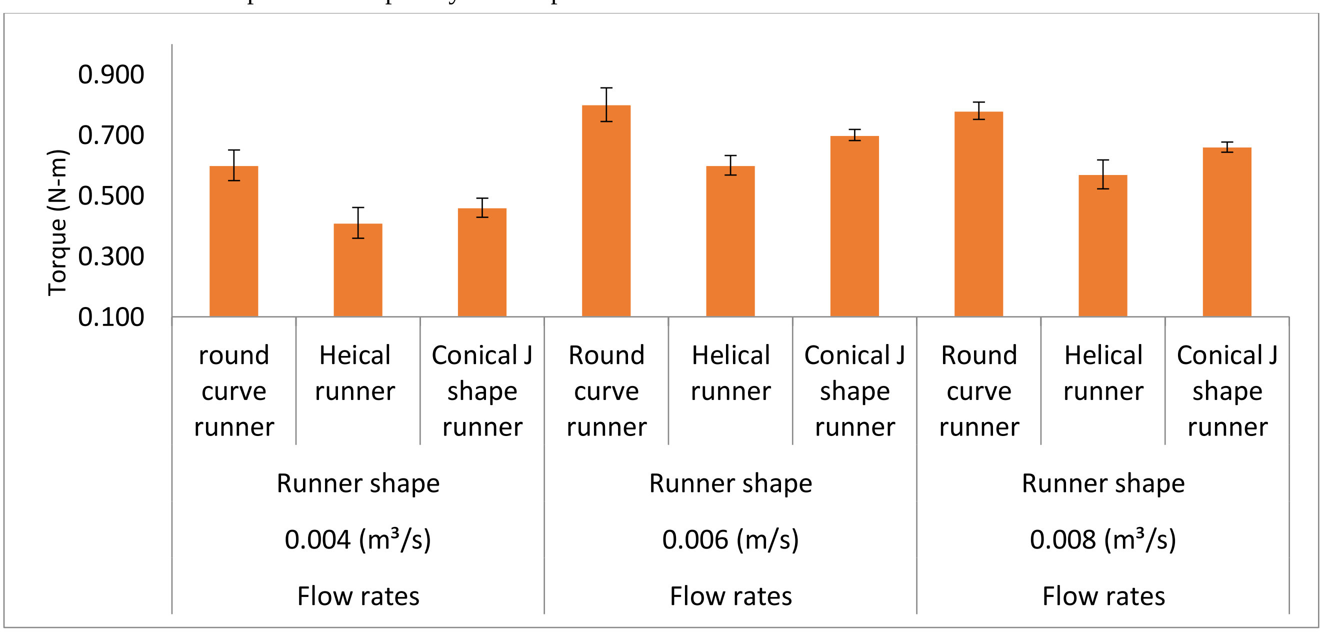

Figure 5. Effect of runner shape on torque

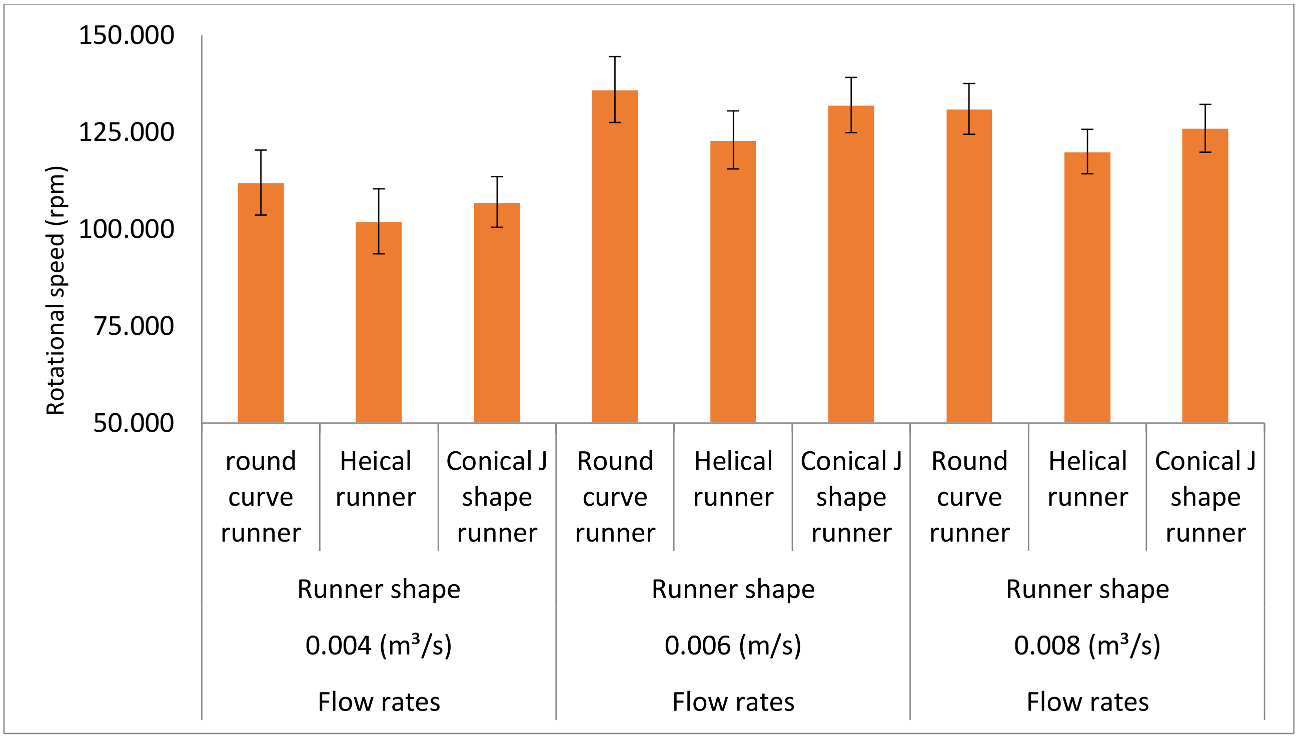

Figure 6. Effect of runner shape on rotational speed

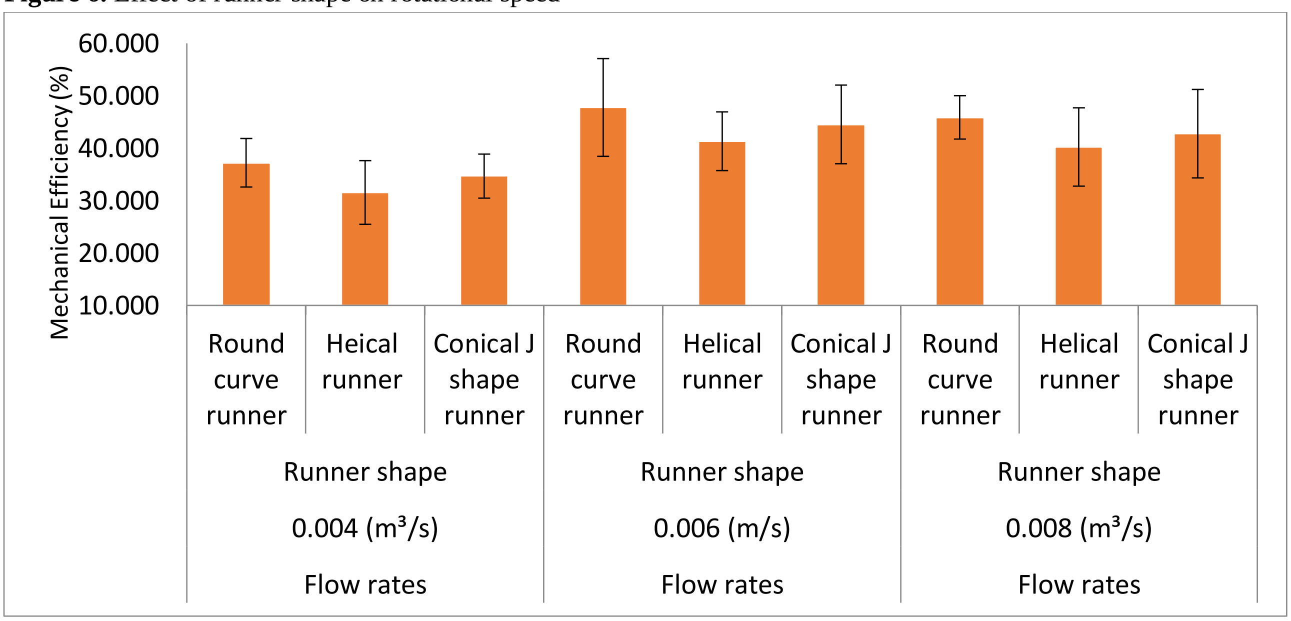

Figure 7. Effect of runner shape on mechanical efficiency

Conclusion

In the current study, the numerical and experimental investigation has been carried out in a conical basin of Gravitational water vortex turbine with three different runners shape configurations. The performance parameters are rotational speed, torque, and mechanical efficiency. The key findings of the above numerical and experimental study are summarized as follows;

The CFD analysis on Gravitational water vortex turbine runner blades showed that more significant water pressure was inserted on the blades of round curved runner blades. When the load on the turbine increased, the runner's rotational speed decreased. All the runners perform better in a median applied torque which resultants higher rotational speed. The performance parameters of the round-curved runner are more significant among all the runners through different flow conditions in terms of rotational speed, brake torque, and efficiency. The blades of the round curved runner give an efficiency of 48.02 %, while the blades of the conical J shape runner and helical runner give an efficiency of 42.17 % and 38.64 %, respectively.

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Data availability: The data presented in this study are available on request

Authors contribution: Conceptualization, A.S.; methodology, A.S, A.N, R.M,; investigation, A.S, A.N, R.M, W.A,; writing- original draft preparation, A.S, W.A, writing- review and editing, A.N, R.M. All authors have read and agreed to the published version of the manuscript.

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REVIEW ARTICLE

A Review on Human-Robot Interaction and User Experience in Smart Robotic Wheelchairs

Sushil Kumar Sahoo[1,*], Bibhuti Bhusan Choudhury[2]

[1]Biju Patnaik University of Technology (BPUT), Rourkela, Odisha, India
[2]Department of Mechanical Engineering, Indira Gandhi Institute of Technology (IGIT), Sarang, Odisha, India

Corresponding Author: Sushil Kumar Sahoo: sushilkumar00026@gmail.com
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Abstract

This review research paper provides an analysis of the current state of Human-Robot Interaction (HRI) and User Experience (UX) in the context of smart robotic wheelchairs. It explores the advancements in HRI techniques, including multimodal interfaces, gesture recognition, voice commands, and brain-computer interfaces, and evaluates their impact on user experience factors such as usability, learnability, efficiency, and satisfaction. The paper discusses the role of artificial intelligence and machine learning in enhancing HRI capabilities and personalization of wheelchair behavior. The review highlights gaps in current research and identifies future directions to improve the immersive experience of smart wheelchair users. Overall, this comprehensive review contributes to a deeper understanding of the factors influencing user acceptance, satisfaction, and system performance, guiding the development of more intuitive and user-centered smart robotic wheelchairs for individuals with mobility impairments.

Keywords: Smart Robotic Wheelchairs**,** Assistive Technology**,** Multimodal Interfaces**,** Brain-Computer Interfaces**,** User Satisfaction

Introduction

The need for smart robotic wheelchairs has become increasingly apparent in recent years, driven by the growing demand to improve the quality of life and independence of individuals with mobility impairments. Traditional manual wheelchairs have limitations in terms of maneuverability, control, and interaction, leading to challenges in performing daily activities and engaging in social interactions (Sahoo and Choudhury, 2021). Smart robotic wheelchairs offer a promising solution by integrating advanced technologies such as robotics, artificial intelligence, and human-robot interaction to enhance mobility, accessibility, and user experience.

One of the primary motivations for developing smart robotic wheelchairs is to provide individuals with greater autonomy and independence in navigating their environment (Padfield et al., 2023). These wheelchairs are equipped with sensors and intelligent control systems that enable autonomous navigation and obstacle detection, allowing users to move safely and efficiently in various indoor and outdoor environments. By reducing the reliance on caregivers or assistance, smart robotic wheelchairs empower individuals with disabilities to have greater control over their own mobility, boosting their self-confidence and overall well-being (Gracia et al., 2023).

Moreover, smart robotic wheelchairs address the need for improved human-robot interaction. Conventional wheelchairs often require significant physical effort and manual control, which can be challenging for individuals with limited upper body strength or dexterity. Smart robotic wheelchairs offer intuitive interfaces, such as voice commands, gesture recognition, or brain-computer interfaces, enabling users to control the wheelchair effortlessly and efficiently (Houssein et al., 2022). These advanced interaction modalities enhance the user experience, making the wheelchair operation more natural, personalized, and user-friendly.

Additionally, smart robotic wheelchairs aim to provide a higher level of adaptability and customization. Each individual has unique mobility requirements and preferences. Smart wheelchairs can learn from user behavior, adapt their movement patterns, and personalize their responses accordingly (Sahoo and Choudhury, 2023a). For instance, they can adjust the speed, acceleration, or turning radius based on the user's comfort level or specific needs. This adaptability ensures a more tailored and comfortable experience for wheelchair users, enhancing their overall satisfaction and acceptance of the technology.

The development and adoption of smart robotic wheelchairs address the pressing need to enhance mobility, independence, and user experience for individuals with mobility impairments. By integrating advanced technologies and focusing on human-robot interaction, these wheelchairs offer intuitive control interfaces, autonomous navigation, adaptability, and customization to meet the unique needs of each user. As research and innovation in this field continue to progress, smart robotic wheelchairs hold immense potential in revolutionizing mobility assistance and improving the quality of life for individuals with disabilities.

Significance of the proposed study

The significance of focusing on Human-Robot Interaction (HRI) and User Experience (UX) in smart robotic wheelchairs lies in their potential to enhance independence, accessibility, and overall user satisfaction for individuals with mobility impairments. By developing intuitive interfaces, personalized interactions, and adaptive behaviors, these advancements contribute to the following key aspects:

- Independence and Mobility: Smart robotic wheelchairs equipped with advanced HRI techniques empower users with greater control, allowing them to navigate their environment independently (Machado et al., 2023). This promotes self-reliance, boosts confidence, and improves overall mobility for individuals with disabilities.
- Accessibility and Inclusion: By integrating multimodal interfaces and considering diverse user needs, smart robotic wheelchairs ensure accessibility for individuals with varying abilities and preferences(Sahoo and Choudhury, 2023b). These wheelchairs enhance inclusion, enabling a wider range of users to effectively interact with and operate the technology.
- User Satisfaction and Acceptance: Focusing on UX in smart robotic wheelchairs leads to improved user satisfaction, acceptance, and adoption of these assistive devices(Sahoo and Choudhury, 2023c). Intuitive interfaces, easy learnability, and personalized experiences contribute to higher levels of user satisfaction, resulting in increased user acceptance and long-term use.
- Personalization and Adaptability: Smart robotic wheelchairs that employ AI and machine learning algorithms can adapt to individual user preferences, providing a tailored experience (Hemmati and Rahmani, 2022). By personalizing movement patterns and responses, these wheelchairs enhance comfort, efficiency, and overall user experience.

Focusing on HRI and UX in smart robotic wheelchairs significantly improves the quality of life for individuals with mobility impairments. By promoting independence, accessibility, user satisfaction, safety, and social acceptance, these advancements contribute to a more inclusive society and empower individuals to lead fulfilling lives.

Objective for the proposed study

The objective of this review research paper is to comprehensively analyze and evaluate the current state of research on Human-Robot Interaction (HRI) and User Experience (UX) in the domain of smart robotic wheelchairs. The paper aims to achieve the following specific objectives:

- To summarize and synthesize recent advancements in HRI techniques and UX considerations in smart robotic wheelchairs, including multimodal interfaces, gesture recognition, voice commands, brain-computer interfaces, and adaptive behaviors.
- To evaluate the impact of different HRI strategies on user experience factors such as usability, learnability, efficiency, and satisfaction in the context of smart robotic wheelchairs.
- To provide insights and recommendations to guide researchers, engineers, and designers in developing more intuitive, user-centered, and accessible smart robotic wheelchairs, with a

focus on enhancing user satisfaction, acceptance, and overall system performance.

By achieving these objectives, this review research paper aims to contribute to a deeper understanding of the current state-of-the-art in HRI and UX in smart robotic wheelchairs, and provide valuable insights for future research and development in this rapidly evolving field.

Literature review

Smart robotic wheelchairs have emerged as a promising solution for enhancing mobility and independence in individuals with mobility impairments. This literature review aims to provide an overview of the current state of research on smart robotic wheelchairs, focusing on the advancements in technology, human-robot interaction (HRI), user experience (UX), and the impact on users' quality of life.

Smart robotic wheelchairs incorporate advanced technologies such as robotics, artificial intelligence, and sensor systems to improve functionality and user experience. Torres-Vega et al. (2023) developed a smart wheelchair with a visual tracking system that uses computer vision algorithms to detect and track objects, allowing for autonomous navigation. This technology enables users to navigate crowded environments safely. Effective human-robot interaction plays a vital role in improving user experience in smart robotic wheelchairs. Sadi et al. (2022) investigated the use of gesture recognition techniques in wheelchair control. Their study demonstrated that gesture-based control interfaces enhanced user satisfaction and provided a more intuitive interaction modality.

Usability, learnability, efficiency, and satisfaction are crucial aspects of user experience in smart robotic wheelchairs. Zhang et al. (2023) conducted a study to evaluate the usability and user satisfaction of a smart robotic wheelchair with voice command capabilities. The results showed that the voice command interface improved the ease of use and overall satisfaction of the users. Personalizing smart robotic wheelchairs based on individual user needs and preferences is essential for enhancing user experience. Darko et al. (2022) proposed a personalized control system for smart wheelchairs using machine learning techniques. Their system adapted the control parameters to individual user characteristics, leading to improved comfort and usability.

Previous studies on Human-Robot Interaction

Smart robotic wheelchairs have revolutionized the field of assistive technology by integrating robotic capabilities into traditional wheelchairs, providing enhanced mobility and independence for individuals with mobility impairments. Effective human-robot interaction (HRI) is critical for optimizing the control, navigation, and collaboration between users and smart robotic wheelchairs.

Several challenges arise in achieving seamless HRI in smart robotic wheelchairs. Control interfaces play a vital role in facilitating user operation, and conventional methods such as joysticks and touchscreens have been widely used (Xu et al., 2023). However, recent developments have explored novel approaches, including voice commands and gesture recognition, to enhance usability and accessibility (Lv et al., 2020). Navigation and obstacle avoidance are crucial aspects of smart robotic wheelchairs, demanding advanced sensor technologies such as cameras, LiDAR, and ultrasonic sensors (Sahoo and Goswami, 2023). Path planning algorithms and collision avoidance mechanisms contribute to safe and efficient navigation (Ntakolia et al., 2023). Adaptability and personalization are essential for accommodating individual user preferences and capabilities. Adjustable seating positions and customizable control interfaces have been incorporated to enhance user comfort and satisfaction (Avutu et al., 2023). Feedback and communication mechanisms, including auditory, visual, and haptic feedback, enable effective communication between the user and the wheelchair, conveying vital information about the wheelchair's status and environment (Su et al., 2023). Safety and trust are paramount, and features such as collision detection, emergency stop mechanisms, and fail-safe systems ensure user safety and build trust in the technology (Zacharaki et al., 2020).

Technological advancements have greatly influenced HRI in smart robotic wheelchairs. Machine learning and artificial intelligence techniques have enabled adaptive behavior and improved user-machine interaction (Tomari et al., 2012). Sensor fusion and perception algorithms have enhanced the wheelchair's perception capabilities, enabling accurate obstacle detection and environment understanding (Pradeep et al., 2022).

Past studies on User Experience

Smart robotic wheelchairs have revolutionized the field of assistive technology, providing individuals with mobility impairments enhanced mobility and independence. User experience (UX) plays a critical role in the acceptance and long-term use of these devices. Several factors contribute to the overall user experience in smart robotic wheelchairs. Understanding these factors is crucial for designing user-centered systems that meet the unique needs and preferences of wheelchair users.

The ease of use and learnability of smart robotic wheelchairs are essential for ensuring that users can operate the device intuitively and with minimal training (Poirier et al., 2023). Intuitive control interfaces and clear instructions contribute to a positive user experience, enabling individuals to navigate and control the wheelchair with confidence.

Comfort and ergonomics play a significant role in enhancing the user experience. Wheelchair users often spend extended periods in their chairs, making factors such as proper cushioning, lumbar support, and adjustability critical for user comfort and well-being (Sahoo and Goswami, 2024). Customizable seating positions and ergonomic design elements further enhance user satisfaction. Safety and reliability are paramount concerns for wheelchair users. Smart robotic wheelchairs should incorporate robust safety features, including collision detection, emergency stop mechanisms, and fail-safe systems (Graf and Eckstein, 2023). Ensuring user safety and building trust in the technology contribute to a positive user experience and promote user acceptance.

Factors such as ease of use, comfort, safety, aesthetics, and long-term engagement play crucial roles in enhancing the overall user experience. Designing user-centered systems that address these factors is essential for ensuring user acceptance and satisfaction. Future research should focus on refining and improving these aspects of UX in smart robotic wheelchairs, thereby empowering individuals with mobility impairments and enhancing their quality of life.

Research gap and Novelty

Despite the significant advancements in the field of smart robotic wheelchairs, there are still several research gaps that need to be addressed. One prominent research gap lies in the limited focus on real-world deployment scenarios. While many existing studies on human-robot interaction (HRI) and user experience (UX) in smart robotic wheelchairs have been conducted in controlled laboratory settings, the practical usability and effectiveness of these devices in real-world environments remain largely unexplored. Factors such as varying environmental conditions, social interactions, and complex navigation scenarios need to be considered to ensure the seamless integration of smart robotic wheelchairs into users' daily lives.

Another research gap is the lack of long-term user studies. Most studies have focused on short-term evaluations, providing valuable insights into immediate user experiences with smart robotic wheelchairs. However, to truly understand the impact of these devices on user well-being, user acceptance, and continued use, it is essential to conduct long-term user studies. These studies can shed light on the sustained usability, user satisfaction, and quality of life improvements that individuals with mobility impairments experience over extended periods of time. Additionally, there is a need for a more comprehensive user-centered design approach in the development of smart robotic wheelchairs. While some studies have incorporated user preferences and needs into the design process, a more systematic and inclusive approach is required. Involving end-users, such as individuals with mobility impairments and healthcare professionals, from the early stages of design and development can ensure that smart robotic wheelchairs truly meet their requirements, expectations, and desires.

This review paper brings together the fields of human-robot interaction (HRI) and user experience (UX) within the context of smart robotic wheelchairs, offering novel insights into their interplay. By comprehensively integrating HRI and UX, this paper provides a holistic understanding of how effective interaction influences user satisfaction and overall experience with these devices. The paper's novelty lies in its identification and highlighting of the research gaps that currently exist in the literature on HRI and UX in smart robotic wheelchairs. By pinpointing the need for real-world deployment studies, long-term user evaluations, and a more comprehensive user-centered design approach, it offers a roadmap for future research in this field. These identified research gaps create opportunities for researchers, engineers, and designers to explore and address these areas, ultimately advancing the field of smart robotic wheelchairs.

Furthermore, this review paper goes beyond academic discussions and offers practical implications for the design and development of smart robotic wheelchairs. By discussing key factors influencing HRI and UX, such as control interfaces, navigation capabilities, adaptability, feedback systems, safety features, and aesthetics, it provides actionable recommendations. These practical insights can guide researchers and designers in creating user-centered smart robotic wheelchair systems that are tailored to the unique needs and preferences of individuals with mobility impairments. By addressing these research gaps and providing practical insights, this review paper contributes to the advancement of HRI and UX in the field of smart robotic wheelchairs. It sets the stage for further research, development, and innovation, ultimately improving the lives of individuals with mobility impairments by promoting their independence, mobility, and overall well-being.

Human-Robot Interaction in Smart Robotic Wheelchairs

Human-robot interaction (HRI) plays a crucial role in the design and operation of smart robotic wheelchairs, offering individuals with mobility impairments enhanced mobility, independence, and improved quality of life. Smart robotic wheelchairs integrate robotic capabilities and advanced technologies, enabling seamless interaction between users and the wheelchair. Effective HRI in these devices involves designing intuitive control interfaces, enabling safe and efficient navigation, providing personalized and adaptive functionalities, and promoting user satisfaction. This short introduction sets the stage for exploring the significance of HRI in smart robotic wheelchairs, highlighting the key challenges, technological advancements, and opportunities for improving the user experience.

Gesture recognition interfaces

Gesture recognition interfaces are an emerging technology in the field of human-robot interaction (HRI) for smart robotic wheelchairs. These interfaces allow users to control and interact with the wheelchair through natural hand and body movements, offering an intuitive and accessible means of operation (Savur and Sahin, 2023). Gesture recognition interfaces utilize computer vision and machine learning techniques to interpret and understand user gestures, enabling the wheelchair to respond accordingly.

The process of gesture recognition involves multiple stages. First, a sensor, such as a camera or depth sensor, captures the user's movements. Computer vision algorithms then extract relevant features from the captured data, such as hand position, orientation, and motion trajectories (Soraa, 2023). These features are then mapped to predefined gestures or commands through machine learning algorithms, which classify and interpret the user's intentions.

Gesture recognition interfaces offer several advantages in the context of smart robotic wheelchairs. Firstly, they provide a more natural and intuitive means of interaction, mimicking human-human communication. Users can express their commands and preferences through familiar gestures, reducing the learning curve and cognitive load associated with other control interfaces. This can be particularly beneficial for individuals with limited dexterity or motor control. Moreover, gesture recognition interfaces enhance accessibility, as they do not require physical contact or fine motor skills to operate. Users can interact with the wheelchair using larger body movements or gestures, accommodating a wide range of physical abilities. This promotes inclusivity and empowers individuals with varying levels of mobility impairments to independently control their wheelchairs.

Furthermore, gesture recognition interfaces allow for hands-free operation, freeing the user's hands for other tasks or activities. This can be particularly valuable in situations where users need to simultaneously manipulate objects or interact with their environment while operating the wheelchair (Sahoo et al., 2023). For example, individuals with limited upper-body strength can use gestures to control the wheelchair without the need for physical exertion. While gesture recognition interfaces offer significant potential, they also present some challenges. Variability in user gestures, lighting conditions, and occlusions can affect the accuracy and reliability of the recognition system. Robust computer vision algorithms and machine learning models are necessary to handle these challenges and ensure accurate gesture interpretation.

Gesture recognition interfaces offer a promising approach to human-robot interaction in smart robotic wheelchairs. They provide an intuitive, accessible, and hands-free means of controlling the wheelchair, enabling individuals with mobility impairments to operate their devices with greater ease and independence. As advancements in computer vision and machine learning continue to evolve, gesture recognition interfaces have the potential to enhance the user experience and improve the overall usability of smart robotic wheelchairs.

Voice command interfaces

Voice command interfaces are an increasingly prevalent technology in the field of human-robot interaction (HRI) for smart robotic wheelchairs. These interfaces allow users to control and interact with their wheelchairs through spoken commands, providing a natural and hands-free means of operation. Voice command interfaces utilize automatic speech recognition (ASR) technology to convert spoken words into actionable commands, enabling seamless communication between users and their wheelchairs.

The process of voice command recognition involves several stages. Firstly, the user speaks a command or instruction, which is captured by a microphone or voice input device. The recorded speech is then processed by ASR algorithms, which convert the audio signals into textual representations. Natural language understanding (NLU) techniques are applied to interpret the meaning and intent behind the recognized text. These algorithms analyze the command, extract relevant information, and map it to predefined actions or functionalities within the wheelchair's control system (Huq et al., 2022). Voice command interfaces offer several benefits in the context of smart robotic wheelchairs. Firstly, they provide a natural and intuitive mode of interaction, mimicking human-human communication. Users can express their commands and preferences using familiar language, reducing the learning curve and cognitive load associated with other control interfaces (Sahoo and Choudhury, 2022). This can be particularly advantageous for individuals with limited dexterity or motor control, as it eliminates the need for physical manipulation of control devices.

Moreover, voice command interfaces enhance accessibility, as they do not require physical contact or fine motor skills to operate. Individuals with limited hand function or mobility impairments can easily control their wheelchairs using voice commands, promoting inclusivity and independence. This feature is particularly valuable in situations where users may have difficulty operating traditional joystick-based interfaces or touchscreens. Additionally, voice command interfaces offer hands-free operation, freeing the user's hands for other tasks or activities. Users can control their wheelchairs while simultaneously manipulating objects, carrying items, or performing other daily activities. This flexibility improves user autonomy and allows for multitasking in various environments (Liu et al., 2021).

However, voice command interfaces also present challenges. Accurate speech recognition is a critical factor for successful operation. Variability in speech patterns, accents, background noise, and environmental conditions can impact the accuracy of recognition systems. Robust ASR and NLU algorithms are necessary to handle these challenges and ensure reliable and accurate command interpretation. Another consideration is the system's response time. Users expect immediate and accurate responses to their voice commands. Therefore, voice command interfaces should be designed to minimize latency and provide real-time feedback, allowing users to gauge the system's understanding and responsiveness. Voice command interfaces offer a promising approach to human-robot interaction in smart robotic wheelchairs. They provide a natural, hands-free, and accessible means of controlling the wheelchair, enabling individuals with mobility impairments to operate their devices with ease and independence. As advancements in ASR and NLU technologies continue to evolve, voice command interfaces have the potential to enhance the user experience, improve usability, and foster increased autonomy for users of smart robotic wheelchairs.

Brain-computer interfaces

Brain-computer interfaces (BCIs) represent an advanced and cutting-edge technology in the field of human-robot interaction (HRI) for smart robotic wheelchairs. BCIs establish a direct communication channel between the human brain and the wheelchair's control system, enabling individuals with severe mobility impairments to control their wheelchairs using neural signals (Masengo et al., 2023). This technology holds tremendous potential for enhancing independence and quality of life for individuals with limited or no motor function.

BCIs operate by capturing and interpreting the brain's electrical activity, typically using electroencephalography (EEG) or invasive implants. EEG-based BCIs use a cap or electrodes placed on the user's scalp to record electrical signals generated by the brain. These signals are then processed and decoded using advanced signal processing and machine learning algorithms. Invasive BCIs involve the implantation of electrodes directly into the brain tissue to capture neural activity with higher precision (Xu et al., 2019). The decoding algorithms of BCIs translate the recorded neural signals into actionable commands for the wheelchair. This requires sophisticated pattern recognition techniques to accurately identify the user's intended actions or movements based on the neural signals. Machine learning algorithms play a vital role in training the BCI system to recognize specific brain patterns associated with different commands. BCIs offer several advantages in the context of smart robotic wheelchairs. Firstly, they enable individuals with severe motor impairments, such as spinal cord injuries or neuromuscular disorders, to regain control and autonomy over their mobility. By bypassing the traditional pathways of motor control, BCIs provide an alternative communication channel that directly taps into the user's intentions.

Furthermore, BCIs offer a high level of precision and fine-grained control (Yenugula et al., 2023). Users can perform complex commands, such as navigating through tight spaces, turning, or stopping, with precise and nuanced control using their neural signals. This level of control is particularly important for tasks that require precise movements and spatial awareness.

Moreover, BCIs can provide a faster and more efficient means of communication compared to traditional control interfaces. Once the user becomes proficient in operating the BCI system, the translation from brain signals to wheelchair commands can occur rapidly and seamlessly, minimizing response time and allowing for real-time control (Belkacem et al., 2020). Brain-computer interfaces offer a groundbreaking approach to human-robot interaction in smart robotic wheelchairs. They provide individuals with severe motor impairments the ability to control their wheelchairs directly through their neural signals, offering unprecedented independence and mobility. Ongoing research and advancements in signal processing, machine learning, and neural decoding techniques hold the promise of further improving the accuracy, reliability, and usability of BCIs in the context of smart robotic wheelchairs.

Multimodal interaction strategies

Multimodal interaction strategies are a powerful approach in the field of human-robot interaction (HRI) for smart robotic wheelchairs. These strategies combine multiple modes of communication, such as speech, gestures, touch, and visual cues, to enhance the interaction between users and their wheelchairs. By incorporating multiple modalities, multimodal interaction strategies aim to provide more robust, flexible, and natural means of communication and control. The combination of different modalities allows users to leverage their preferred modes of communication and interact with the wheelchair in a more intuitive and personalized manner. For example, users can simultaneously use speech commands, gestures, and touch inputs to convey their intentions and preferences to the wheelchair (berg and Lu, 2020). This multimodal approach accommodates individual differences in user capabilities, preferences, and environmental contexts, providing a more inclusive and adaptable interaction framework.

Multimodal interaction strategies often utilize machine learning algorithms to process and interpret data from multiple modalities. These algorithms can analyze and integrate information from different sources to generate a comprehensive understanding of the user's intent. For example, speech recognition algorithms can be combined with gesture recognition and visual tracking techniques to create a multimodal fusion approach that enhances the accuracy and reliability of user commands. The benefits of multimodal interaction strategies in smart robotic wheelchairs are manifold. Firstly, they enhance the naturalness and flexibility of communication. By integrating multiple modes, users can express themselves using a combination of verbal cues, physical gestures, and visual references, mirroring natural human-human communication. This promotes a more intuitive and engaging interaction experience (Yenugula et al., 2024).

Secondly, multimodal interaction allows for redundancy and error correction. In situations where one modality may be ambiguous or noisy, other modalities can serve as backup or provide additional context. For instance, if a speech command is unclear, the wheelchair can rely on gestures or visual cues to disambiguate the user's intention. This redundancy improves robustness and reduces the likelihood of misinterpretation. Furthermore, multimodal interaction can enhance accessibility and inclusivity. By offering multiple means of interaction, individuals with diverse abilities and preferences can engage with the wheelchair more effectively. Users with speech impairments may rely on gestures or touch inputs, while those with limited mobility may utilize voice commands and visual cues (Alonso et al., 2021). This flexibility enables a broader range of users to interact with the wheelchair comfortably.

Multimodal interaction strategies offer a powerful framework for human-robot interaction in smart robotic wheelchairs. By combining multiple modalities, these strategies enhance naturalness, flexibility, robustness, and inclusivity of communication and control. Ongoing research in multimodal fusion, machine learning, and sensor technologies will continue to advance the effectiveness and usability of multimodal interaction strategies, further improving the interaction experience and empowering individuals with mobility impairments to control their wheelchairs with greater ease and independence.

User Experience Considerations

User experience considerations are paramount in the design of robotic wheelchairs, focusing on ensuring optimal usability, comfort, safety, personalization, integration, and long-term user satisfaction. By prioritizing intuitive control interfaces, comfortable seating systems, reliable obstacle detection, and collision avoidance, as well as offering customization options and seamless integration into users' environments, robotic wheelchairs can enhance the overall user experience. These considerations aim to empower individuals with mobility impairments, promoting their independence, mobility, and well-being.

Usability evaluation methods

Usability evaluation methods are essential in assessing the user experience and effectiveness of robotic wheelchairs. These methods involve various techniques and approaches that provide valuable insights into the usability, efficiency, and user satisfaction with the wheelchair's design and functionality. Here, we discuss some commonly used usability evaluation methods in detail.

- User Testing: User testing involves observing and collecting feedback from users as they interact with the robotic wheelchair. This can be done through structured tasks or scenarios that simulate real-world usage (Di et al., 2013). Observations, interviews, and questionnaires are used to gather qualitative and quantitative data on aspects such as ease of use, task completion time, and user satisfaction. User testing provides direct insights into the strengths and weaknesses of the wheelchair's design and usability from the user's perspective.
- Expert Evaluation: Expert evaluation involves usability experts or domain specialists assessing the wheelchair's design and functionality based on established usability heuristics or guidelines (Zahabi et al., 2022). These experts evaluate the system using their expertise and experience to identify potential usability issues, cognitive load, and interaction complexities. Expert evaluation provides valuable insights into design flaws and areas for improvement, complementing user feedback.
- Cognitive Walkthrough: Cognitive walkthroughs focus on the user's cognitive processes and decision-making while using the robotic wheelchair. Evaluators analyze each step or interaction in a task and assess whether the user's goals, information requirements, and actions align with the wheelchair's design (Czaja and Ceruso, 2022). This method helps identify potential cognitive challenges, information gaps, and usability obstacles that may impede the user's successful completion of tasks.
- Task Analysis: Task analysis involves breaking down complex tasks into smaller subtasks or steps to understand the cognitive and physical demands placed on the user. By examining the sequence of actions required to accomplish tasks, task analysis identifies potential bottlenecks, redundancies, or gaps in the wheelchair's workflow. This method helps optimize task design and streamline user interactions, ultimately enhancing usability and efficiency.

These usability evaluation methods, when used individually or in combination, provide a comprehensive understanding of the wheelchair's usability, user satisfaction, and areas for improvement. By incorporating these evaluation methods into the design and development process, robotic wheelchair designers can iteratively refine and optimize the system to meet the specific needs and preferences of users, ultimately enhancing the overall user experience and promoting user independence and mobility.

Learnability and efficiency

Learnability and efficiency are key considerations in the design and evaluation of robotic wheelchairs' user experience. Learnability refers to the ease with which users can learn to operate the wheelchair effectively, while efficiency focuses on the speed and accuracy with which users can accomplish tasks using the wheelchair. Both factors are crucial in ensuring that users can quickly adapt to the wheelchair's functionality and interact with it in a productive and efficient manner.

Learnability can be enhanced through several design considerations. First, the user interface should be intuitive and provide clear feedback to guide users in understanding how to control the wheelchair. Clear and concise instructions, visual cues, and user-friendly interfaces help users quickly grasp the necessary actions and operations. The system should be designed with simplicity in mind, avoiding unnecessary complexity or overwhelming options that could hinder the learning process. Training and education also play a vital role in promoting learnability. Providing comprehensive user manuals, tutorials, or interactive training sessions can familiarize users with the wheelchair's features, controls, and functionalities (WHO, 2023). In addition, ongoing support, such as accessible helplines or online resources, can be valuable for users to address any questions or difficulties they may encounter during their initial learning phase.

Efficiency, on the other hand, focuses on optimizing the speed and accuracy of user interactions with the wheelchair. Efficient wheelchair design entails minimizing the number of steps or actions required to complete tasks, reducing cognitive load, and streamlining user workflows. This can be achieved by leveraging automation, intelligent algorithms, and adaptive control systems that anticipate user needs and proactively assist with task completion (Gowran et al., 2022). By prioritizing learnability and efficiency, designers of robotic wheelchairs can create systems that enable users to quickly grasp the wheelchair's operation, maximize their productivity, and achieve their desired tasks with speed and accuracy. This ensures a positive user experience, empowers users with greater independence, and facilitates their integration into various environments with enhanced mobility.

User satisfaction assessment

User satisfaction assessment is a critical aspect of evaluating the user experience of robotic wheelchairs. It involves gathering feedback from users to understand their perceptions, preferences, and overall satisfaction with the wheelchair's design, functionality, and performance (Bouffard et al., 2022). Assessing user satisfaction helps identify strengths, weaknesses, and areas for improvement, allowing designers to tailor the wheelchair's features and interactions to meet users' needs and expectations. There are various methods and techniques for assessing user satisfaction in the context of robotic wheelchairs:

- Surveys and Questionnaires: Surveys and questionnaires provide a structured approach to collect user feedback. Standardized scales, such as the System Usability Scale (SUS) or the Technology Acceptance Model (TAM), can be employed to measure user satisfaction, perceived ease of use, and perceived usefulness. Open-ended questions allow users to provide detailed feedback, suggestions, and specific areas of concern or satisfaction.
- Interviews: Interviews offer an opportunity for in-depth discussions with users, allowing researchers to delve into their experiences, perceptions, and preferences regarding the wheelchair. Semi-structured or structured interviews can be conducted to explore specific aspects of user satisfaction, usability challenges, or areas where the wheelchair excels. These interviews provide rich qualitative insights and uncover nuanced perspectives.
- Usability Testing: Usability testing involves users performing specific tasks or scenarios using the robotic wheelchair while researchers observe and collect data. User actions, task completion time, errors, and subjective feedback are recorded to assess usability and satisfaction. This method provides both quantitative and qualitative data, offering insights into the effectiveness and efficiency of the wheelchair in meeting user needs.
- Post-use Evaluation: After users have interacted with the robotic wheelchair for a certain period, post-use evaluation methods can be employed to capture long-term user satisfaction. These methods may include follow-up surveys, interviews, or focus groups to gather feedback on user experiences over an extended duration. Longitudinal assessments enable the identification of evolving needs, challenges, and satisfaction levels as users gain familiarity and experience with the wheelchair.

- User Experience Metrics: User experience metrics, such as the Net Promoter Score (NPS) or the Customer Satisfaction Score (CSAT), provide quantitative measures of overall user satisfaction and loyalty. These metrics allow for benchmarking and comparison across different iterations or versions of the wheelchair, enabling designers to track improvements over time.

By employing a combination of these assessment methods, researchers and designers can gain comprehensive insights into user satisfaction with robotic wheelchairs. This information can be used to identify usability issues, areas of improvement, and opportunities to enhance user satisfaction. Regular user satisfaction assessments and continuous user involvement throughout the design process facilitate iterative improvements, leading to the development of more user-centered and satisfying robotic wheelchairs.

User-centered design principles

User-centered design (UCD) principles are fundamental guidelines that focus on designing products, such as robotic wheelchairs, with the needs, preferences, and capabilities of users at the forefront (Zablocki et al., 2022). UCD aims to create intuitive, usable, and satisfying experiences for individuals with mobility impairments, placing them at the center of the design process. Here, we explore key UCD principles in detail.

- User Involvement: UCD emphasizes active involvement of users throughout the design process. Engaging users in activities such as interviews, observations, and usability testing allows designers to gain insights into their needs, challenges, and aspirations. User feedback and preferences guide the decision-making process, ensuring that the wheelchair's design and features align with the users' goals and expectations.
- User Research: User research involves conducting thorough investigations to understand the target users, their characteristics, contexts, and unique requirements. This research encompasses factors such as physical abilities, cognitive capabilities, lifestyle, and environmental considerations. By gaining a deep understanding of the user base, designers can create solutions that address specific needs and enhance user satisfaction.
- Iterative Design: UCD embraces an iterative approach to design, where solutions are refined through multiple cycles of prototyping, evaluation, and user feedback. Each iteration builds upon previous insights, allowing designers to address usability issues, refine features, and enhance the overall user experience. This iterative process ensures that the final product is well-adapted to users' needs and preferences.
- Accessibility and Inclusivity: UCD emphasizes designing for accessibility and inclusivity, considering the diverse range of users with varying abilities and disabilities. Designers strive to remove barriers and provide equitable access to all users. This involves ensuring physical accessibility, accommodating different cognitive capabilities, and addressing sensory or motor impairments. Design choices such as adjustable seating, multiple control options, and customizable interfaces promote inclusivity.
- Clear and Consistent Interfaces: UCD emphasizes the importance of clear and consistent interfaces that facilitate ease of use and reduce cognitive load. Designers strive to create intuitive control layouts, provide feedback through visual or auditory cues, and use consistent icons or symbols to convey information. By minimizing complexity and providing a familiar and predictable interaction framework, users can quickly understand and navigate the wheelchair's features.
- Feedback and Error Handling: UCD emphasizes the provision of timely and informative feedback to users. The wheelchair should provide clear indications of system status, acknowledge user commands, and communicate error messages effectively. Meaningful feedback helps users understand the system's behavior, recover from errors, and maintain a sense of control and confidence.

By embracing these UCD principles, designers can create robotic wheelchairs that are intuitive, usable, and satisfying for individuals with mobility impairments. UCD promotes an empathetic and holistic approach to design, ensuring that the wheelchair meets the specific needs, preferences, and aspirations of its users, ultimately enhancing their independence, mobility, and overall well-being.

Safety and Trust in Human-Robot Interaction

Safety and trust are critical factors in human-robot interaction (HRI). In HRI, safety refers to the assurance that the robot operates without causing harm to users or its surroundings. It involves robust obstacle detection, collision avoidance, and fail-safe mechanisms to prevent accidents and injuries (Vasconez et al., 2019). Trust, on the other hand, encompasses the user's confidence and belief in the robot's reliability, capabilities, and intentions. Establishing safety and trust in HRI is crucial to ensure user confidence, promote effective collaboration, and enable users to rely on robots for assistance and support.

Collision avoidance and risk mitigation

Collision avoidance and risk mitigation are vital features in smart robotic wheelchairs that aim to ensure user safety and prevent accidents or collisions in various environments. These features leverage advanced sensing technologies, intelligent algorithms, and adaptive control systems to detect and respond to potential obstacles or hazards. Smart robotic wheelchairs employ various sensors, such as proximity sensors, cameras, or lidar, to continuously scan the surrounding environment. These sensors provide real-time data about the wheelchair's surroundings, detecting obstacles, objects, or people in its path. By accurately perceiving the environment, the wheelchair can make informed decisions and take appropriate actions to avoid potential collisions.

The collision avoidance algorithms in smart robotic wheelchairs analyze the sensor data and assess the risk levels associated with detected obstacles. These algorithms calculate the proximity, speed, and trajectory of obstacles relative to the wheelchair, allowing the wheelchair to predict potential collisions and determine the most appropriate course of action. Depending on the situation, the wheelchair may adjust its speed, direction, or halt completely to prevent collisions.

Risk mitigation strategies in smart robotic wheelchairs involve proactive measures to minimize the likelihood or impact of potential accidents. These strategies may include adjusting the wheelchair's speed or acceleration based on the detected risk level, activating additional safety features, or providing timely warnings to the user about potential hazards. By dynamically adapting its behavior to the risk levels, the wheelchair can prioritize user safety and mitigate potential dangers. Continuous research and development in collision avoidance and risk mitigation for smart robotic wheelchairs aim to improve the accuracy, reliability, and effectiveness of these features. Advancements in sensing technologies, machine learning algorithms, and real-time decision-making allow for more robust and adaptive collision avoidance systems, ensuring safer and more secure interactions between users and smart robotic wheelchairs.

Trust-building mechanisms

Trust-building mechanisms in smart robotic wheelchairs are designed to foster a sense of reliability, predictability, and confidence in the interaction between users and the robotic system. These mechanisms aim to establish a trusting relationship between the user and the wheelchair, ensuring smooth and effective collaboration. Several factors contribute to building trust in smart robotic wheelchairs.

- Reliable and Consistent Performance: The wheelchair should consistently demonstrate reliable and accurate performance in its actions and responses. Users should have confidence that the wheelchair will operate as intended, follow commands accurately, and navigate safely. By delivering consistent and predictable performance, the wheelchair builds trust by meeting user expectations and reducing uncertainty.
- Transparent Communication: Transparent communication is crucial in building trust. The wheelchair should provide clear and understandable feedback to the user, conveying its intentions, actions, and status. This includes visual or auditory cues that indicate the wheelchair's current state, planned movements, and any detected obstacles or risks. Transparent communication helps users understand and anticipate the wheelchair's behavior, enhancing trust and facilitating effective collaboration.
- Explainable Decision-Making: Smart robotic wheelchairs often employ complex algorithms and decision-making processes. To build trust, it is important that these decisions are explainable to the user. Users should be able to understand why the wheelchair made a particular choice or took a specific action. Providing explanations or

visualizing the decision-making process can help users feel more involved and informed, promoting trust in the system's capabilities.

- User Control and Override: Allowing users to have a degree of control and override capability enhances trust. Users should feel that they have the ability to intervene, modify, or correct the wheelchair's actions when needed. This can be achieved through intuitive and accessible control interfaces, emergency stop buttons, or manual control options. User control and override mechanisms provide users with a sense of agency and contribute to their trust in the wheelchair's operation.

By incorporating these trust-building mechanisms, smart robotic wheelchairs can create a positive user experience and foster a sense of reliability, transparency, and user confidence. Building trust is essential to maximize user acceptance, collaboration, and satisfaction, enabling individuals with mobility impairments to embrace and benefit from the capabilities of smart robotic wheelchairs.

Ethical considerations and privacy protection

Ethical considerations and privacy protection are crucial aspects to address in the development and deployment of smart robotic wheelchairs. These considerations aim to ensure the responsible use of technology, protect user privacy, and uphold ethical principles in the interaction between users and the robotic system.

- Informed Consent: Obtaining informed consent is essential before deploying smart robotic wheelchairs. Users should be fully informed about the capabilities, limitations, and potential risks associated with the technology. They should have a clear understanding of how their personal data will be collected, used, and protected. Informed consent allows users to make informed decisions and exercise control over their participation in the robotic wheelchair program.
- Privacy Protection: Protecting user privacy is paramount. Smart robotic wheelchairs may collect various types of personal data, such as location information, health data, or user preferences. It is important to implement robust data protection measures to ensure the confidentiality, integrity, and controlled access of user data. Anonymization or pseudonymization techniques can be employed to minimize the risk of re-identification. Data encryption, secure data storage, and access controls help safeguard user privacy.
- Data Minimization: Adhering to the principle of data minimization involves collecting only the necessary data required for the functioning of the smart robotic wheelchair. Unnecessary or excessive data collection should be avoided to minimize privacy risks. By limiting data collection to essential information, the risk of potential data breaches or unauthorized access is reduced.
- Transparency: Ensuring transparency in the operation and use of smart robotic wheelchairs is crucial. Users should have clear visibility into how the wheelchair operates, the data it collects, and how that data is utilized. Transparent communication about the purpose, capabilities, and potential impact of the technology helps users make informed decisions and promotes trust in the system.

By incorporating these ethical considerations and privacy protection measures, smart robotic wheelchairs can operate in a responsible and user-centric manner. Respecting user privacy, promoting transparency, and upholding ethical principles foster trust, enhance user acceptance, and ensure the long-term viability and benefits of smart robotic wheelchairs in improving the lives of individuals with mobility impairments.

Conclusion

This review paper has explored the fascinating field of human-robot interaction (HRI) and user experience in the context of smart robotic wheelchairs. Through an in-depth examination of various aspects, including technology advancements, personalized control, interface design, user satisfaction, and ethical considerations, we have gained valuable insights into the current state and future directions of this rapidly evolving field.

The research gap and novelty in this area lie in the need for further exploration and development of personalized and adaptive features that enhance the user experience and promote independence, safety, and comfort. While significant progress has been made in technology advancements, there is still room for improvement in areas such as navigation algorithms, gesture recognition interfaces, voice command interfaces, and brain-computer interfaces. Additionally, considerations for user satisfaction, usability evaluation, learnability, efficiency, and user-centered design principles have been highlighted as critical factors in the successful design and implementation of smart robotic wheelchairs. Furthermore, the review has shed light on the importance of trust-building mechanisms, safety, and privacy protection in human-robot interaction. Trust, transparency, and user empowerment are fundamental for fostering acceptance, collaboration, and positive user experiences. Ethical considerations, including informed consent, privacy protection, and ethical decision-making, must be at the forefront of the development and deployment of smart robotic wheelchairs to ensure responsible and ethical use of this technology.

Practical Implication

The practical implications of this review paper on human-robot interaction (HRI) and user experience in smart robotic wheelchairs are significant for various stakeholders involved in the design, development, and deployment of these assistive devices. The following practical implications can be drawn from the findings:

- Design Guidelines: The review highlights the importance of user-centered design principles and customization in smart robotic wheelchair development. Designers and engineers can leverage these guidelines to create interfaces, control systems, and adaptive behaviors that prioritize user needs, preferences, and capabilities. By incorporating user feedback throughout the design process, practitioners can ensure that the wheelchair's features and interactions align with user expectations, enhancing overall user experience.
- Technology Advancements: The paper emphasizes the need for ongoing technology advancements in areas such as robotics, sensors, artificial intelligence, and machine learning. Practitioners can stay updated with the latest advancements and innovations to enhance the capabilities and performance of smart robotic wheelchairs. Implementing advanced navigation algorithms, gesture recognition interfaces, voice command interfaces, and brain-computer interfaces can improve the wheelchair's responsiveness, adaptability, and ease of use.
- Safety and Trust: Safety considerations and trust-building mechanisms are crucial practical implications highlighted in the paper. Practitioners should prioritize safety features such as collision avoidance, risk mitigation, and fail-safe mechanisms in smart robotic wheelchair designs. Implementing transparent communication, user control, and explainable decision-making can foster trust between users and the robotic system. By addressing ethical considerations and privacy protection, practitioners can ensure responsible and trustworthy deployment of smart robotic wheelchairs.

These practical implications provide valuable guidance for practitioners and stakeholders in the field of smart robotic wheelchairs. By implementing these recommendations, practitioners can enhance the user experience, improve usability, prioritize safety, and foster trust in the interaction between users and smart robotic wheelchairs.

Limitation

While this review paper provides valuable insights into human-robot interaction (HRI) and user experience in smart robotic wheelchairs, it is important to acknowledge certain limitations:

- Knowledge Cutoff: The review paper's limitations are tied to the knowledge cutoff date, which is the point at which the paper's literature review ends. As an AI language model, my knowledge cutoff is September 2021. Therefore, newer research, technological advancements, or emerging trends beyond this date may not be included in the paper. It is advisable for readers to supplement their understanding by referring to more recent studies and literature.
- Individual Variability: HRI and user experience are highly individualized and subjective. The review paper provides a general overview and discusses common trends and considerations. However, individual user preferences, abilities, and contexts can significantly influence their

experience with smart robotic wheelchairs. It is important to recognize that user experiences may vary, and there may not be a one-size-fits-all solution for every user.

- Lack of Empirical Studies: While the review paper may draw from empirical studies and existing research, the paper itself may not present new empirical findings. It relies on synthesizing and summarizing existing knowledge and research. Therefore, the conclusions and implications drawn from the review are based on the available literature, and further empirical studies are necessary to validate and expand upon the findings.

Despite these limitations, this review paper offers a comprehensive overview of the current state of research in HRI and user experience in smart robotic wheelchairs. It provides a foundation for further exploration, empirical studies, and advancements in the field, guiding future research and development efforts to improve the usability, safety, and overall user satisfaction with these assistive technologies.

Future Scope

The review paper on human-robot interaction (HRI) and user experience in smart robotic wheelchairs opens up several avenues for future research and development. The following future scope can be considered:

- Advanced Sensing Technologies: Future research can focus on integrating advanced sensing technologies into smart robotic wheelchairs. This includes the use of more sophisticated sensors such as 3D cameras, depth sensors, or wearable sensors to improve obstacle detection, object recognition, and environment perception. By enhancing the perception capabilities of the wheelchair, it can navigate complex environments more effectively and ensure user safety.
- Multimodal Interaction: Further exploration of multimodal interaction strategies can be pursued. Combining different modes of communication, such as gesture recognition, voice commands, haptic feedback, or brain-computer interfaces, can enable more intuitive and natural interactions between users and smart robotic wheelchairs. Future research can delve into the development of robust multimodal interfaces that adapt to individual user preferences and abilities.
- Social and Emotional Interaction: Exploring the integration of social and emotional intelligence in smart robotic wheelchairs can be a fascinating avenue for future research. This involves developing algorithms that enable the wheelchair to recognize and respond to user emotions, provide social cues, and engage in more human-like interactions. By incorporating social and emotional aspects, the wheelchair can foster a sense of companionship and support for users.

By pursuing these future research directions, the field of HRI and user experience in smart robotic wheelchairs can continue to evolve, leading to more advanced, user-centric, and inclusive assistive technologies. The future scope encompasses advancements in sensing technologies, multimodal interaction, personalized control, social and emotional interaction, context-aware adaptability, long-term user studies, and ethical considerations, ultimately contributing to the improvement of smart robotic wheelchairs and the well-being of individuals with mobility impairments.

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Conflict of interest

There are no conflicts of interest to disclose, according to the author(s).

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Author Contribution

The idea and design of the study were contributed to by S. K. Sahoo and B. B. Choudhury. S. K. Sahoo wrote the manuscript and helped with the material processing and collecting. The document was modified by Dr. B.B. Choudhury.

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