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Article

# AI Powered Surveillance and Smart Analytics for Security Manpower Optimization in Rail Based Mass Rapid Transit Systems

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**Abstract:** Rail-based Mass Rapid Transit Systems is a backbone of urban infrastructure where security failures can lead to panic among public, creating disaster scenarios. In India, metro rail organizations such as DMRC depends heavily on human-intensive security measures, primarily with CISF for overlooking physical frisking, baggage scanning, patrolling, overseeing surveillance and access control across the stations and allied infrastructures such as Train Depots, Operational Control Centres, etc. Traditional CCTV monitoring utilize about 9% of total deployed security strength, is becoming hard to manage due to rapid growth of metro network, increasing operational costs. This study evaluates the current manpower allocation for CCTV surveillance in DMRC and explores how security staff can be optimized with AI-based surveillance and smart analytics. This study adopts quantitative secondary data design to estimate the manpower required for CCTV surveillance across the operational and sanctioned phases of the DMRC. Findings reveals that adopting AI-powered surveillance could reduce the need for around 1560 dedicated CCTV monitoring staff across the sanctioned network of DMRC, leading to cumulative salary savings of approx. 15,455.64 million INR between 2026 to 2035.

Further, AI-based systems can better spot unusual act, send instant alerts, monitor crowd levels and analyses passenger behavior, helping in efficient disaster preparedness in MRTS network. The study concludes that AI-powered surveillance is an important step in building cost-effective, modern and disaster resilient metro security systems. However, the research also points challenges for successful large scale rollout, including high implementation costs and establishing rules for privacy and ethical use of the technology which need to be managed.

**Keywords:** AI-powered Surveillance, Mass Rapid Transit Systems (MRTS), Manpower Optimization, Security Management, Delhi Metro (DMRC) and Disaster Resilience

## 1. Introduction

Rail-based Mass Rapid Transit Systems (MRTS) are an essential part of urban infrastructure, and their disruption can have wide ranging economic, social and public safety impacts. In India's fast-growing cities, metro rail networks play a vital role in supporting sustainable urban transport solutions, easing road congestion and providing affordable travel to millions of commuters every day. However, open public accessibility, high passenger volumes and continuous operations and maintenance activities make MRTS more exposed to security risks, crowd related incidents and potential emergency situations.

Security in Mass Rapid Transit System has traditionally depended on physical infrastructure, physical surveillance mechanisms and extensive manpower positioning. In Indian metro networks, security responsibilities are jointly handled by between the central armed forces and metro operators, with government agencies such as the Central Industrial Security Force (CISF) and private entities providing Platform Guards and Customer Facilitation Agents (CFAs) responsible for tasks like physical frisking, access control, patrolling in metro premises, passenger assistance, handling passenger nuisance and CCTV monitoring. Although this mechanism has maintained relatively reputed security records, it is now facing increasing pressure due to rapid network growth, higher passenger numbers and limited resources, prompting to adapt upgraded AI based technologies.

Conventional security frameworks largely depend on manual surveillance and fixed pattern of personal deployment. However, contemporary CCTV infrastructures produce massive amount of video data. This data generation is usually so vast and fast that it cannot be effectively observed, interpreted and acted upon in real-time by the human operators. Deployment of security manpower is frequently determined by prescribed standard operating procedures instead of real-time risk indicators, resulting in excess staffing at lower risk points while areas facing greater threats may remain under monitored during heightened risk. Such structural constraints make it more difficult to identify incidents quickly and thus delay response time. Weakening the overall efficiency of managing emergencies or rapidly changing disaster scenarios can be reduced. Recent advances in Artificial Intelligence (AI) have provided path breaking opportunities to enhance security management in Mass Rapid Transit Systems (MRTS). AI-powered surveillance systems can analyse video streams in real-time, identify abnormal behaviours, analyse human activity patterns and generate alerts within seconds. This technique turns the surveillance from traditional simple monitoring into an intelligence driven decision support system based on real time information.

The rapid expansion of the Delhi Metro Rail Corporation has brought to the forefront the increasing demand for scalable and efficient security systems for modern rail-based Mass Rapid Transit Systems (MRTS). The Delhi Metro has grown from a modest network of 64.751 km and 59 stations in Phase I to 374.466 km with 271 operational stations in April 2026 and is expected to grow to 478.917 km with 352 stations by 2031. Managing security across such a large and continuously expanding network through conventional manpower-intensive methods is becoming increasingly difficult. In this scenario, AI-powered surveillance and smart analytics provide a practical and scalable approach by supporting real-time monitoring, faster incident detection, centralized control, and better deployment of security personnel without requiring a proportional increase in manpower. Table 1 outlines DMRC's operational and sanctioned network phases as of 30 April 2026.

**Table 1: Phases of the Delhi Metro and Number of Stations Sanctioned up to 30 April 2026** (Source: DMRC Official Reports)

| **S No.** | **Delhi Metro Phase (Operational Network as on 30.04.2026)** | **Length (km)** | **Station** | **Revenue Year (with projections)** |
|---|---|---|---|---|
| 1 | Phase I | 64.751 | 59 | 2002–2006 |
| 2 | Phase II & Extension | 123.300 | 86 | 2008–2011 |
| 3 | Phase III & Extension | 162.375 | 111 | 2019–2021 |
| 4 | Operational Network up to Phase III | 350.426 | 256 | Till 31.12.2024 |
| 5 | Phase IV (operational in 2025) | 1.810 | 1 | 2025 |
| 6 | Phase IV (operational in 2026) | 22.230 | 14 | 2026 |
| 7 | Total Operational Network (Till 30.04.2026) | 374.466 | 271 | Till 30.04.2026 |
| 8 | Phase IV (Priority Corridor, Under Construction) | 41.150 | 30 | December 2026 |
| 9 | Phase IV (Remaining Corridor, Under Construction) | 47.225 | 39 | 2029 |
| 10 | Total Phase IV [5+6+8+9] | 112.415 | 83 | Till 2029 |
| 11 | Phase V(A) (Sanctioned till 30.04.2026) | 16.076 | 13 | 2031 |
| Overall Total (Operational + projected) [4+10+11] | | 478.917 | 352 | Till 2031 |

In the Indian context, where security personnel deployed in MRTS accounts for a significant share in operational expenditure and the network is projected to expand to numerous stations in the coming decade, AI based technologies provide a real time approach to optimize the manpower while also strengthening emergency preparedness and disaster response mechanisms. Despite these developments, most existing studies on AI-based surveillance mainly examine technical aspects such as detection accuracy, algorithm performance and system reliability. Little focus has been on quantifying the ability of these technologies to enhance manpower planning or lower the long-term operation expenses in rail-based transit systems. Moreover, the relationship between smart surveillance and disaster resilience in high-traffic public transport systems has not been sufficiently studied in the Indian context of operations and policies. This situation highlights an important research gap related to security management, efficient resource utilization and disaster risk mitigation. However, existing literature on AI based surveillance has predominantly concentrated on technical aspects such as algorithmic performance, system robustness and detection accuracy with relatively limited attention paid to their measurable impact on manpower optimisation and reducing long-term operational costs in rail-based transport systems. In addition, the linkage between intelligent surveillance and disaster resilience in MRTS having high footfall has not been adequately examined in the Indian operational and policy context. This poses a critical knowledge gap at the cross-section of security management, resource planning and disaster risk mitigation.

In order to fill this gap, the current research paper discusses the manpower-intensive surveillance system that is currently in place in Indian Mass Rapid Transit Systems, and in particular, the Delhi Metro Rail Corporation (DMRC). It examines how AI-based surveillance, with the assistance of smart data analytics, can enhance the use of security personnel throughout the network. Another objective of the study is to come up with a framework that can be used to improve operational efficiency, minimize long-term operational costs and improve disaster preparedness in rail-based urban transit systems.

The subsequent sections of this paper are structured as follows. Section 2 examines the existing literature and identifies the gaps in conventional CCTV based monitoring mechanism used for managing security across Mass Rapid Transit Systems (MRTS). Section 3 outlines the approach to the evaluation of the current and future manpower needs. Section 4 points out the existing security system in place at the Delhi Metro Rail Corporation. Section 5 describes the data collection and data analysis procedure based on the information obtained through the use of reliable sources like press releases, mobile apps and official websites. Section 6 discusses the results of the analysis and provides the estimated cost involving manpower deployment for CCTV monitoring. Section 7 presents the findings and examines the limitations along with challenges associated with the implementation of AI based monitoring systems. Section 8 concludes the study, whereas Section 9 identifies future prospects and proposes directions for further research.

## 2. Literature review

The exponential and ongoing advancements in Artificial Intelligence (AI), the Internet of Things (IoT), and Machine Learning (ML) are providing solutions for every field including resource management, transportation engineering, surveillance, public safety and human resource management [1,2]. These technologies have proven to be of great importance and transformative potential in various engineering and management fields, paving the way for a new paradigm of data-driven innovation and operational efficiency. Smart infrastructure with AI-enabled integrates data from multiple domains to optimise functioning of cities. AI applications span across smart city domains such as traffic management, public safety and resource allocation [3]. The integration of Artificial Intelligence (AI) in smart infrastructure, particularly in metro and rail transit system, is the need of hour and requires execution with evidences. Empirical studies reveal that traditional security models relying on human manpower are not sustainable in high-density transit environments. Given the volume of passengers and logistical complexity, transitioning to AI-enabled solutions is required to overcome the limitations of human observation and ensure long-term operational efficiency.

### *2.1 Automation, human resources and workforce transformation*

In the current literature, there is a consistent pattern that automation is transforming the nature and shape of skilled jobs instead of fully substituting human employees. [4]. Research indicates that automation not only enhances efficiency in various tasks, but also generates a new need in skills among employees and the necessity of organizations to alter their working behavior. Transition in security contexts often refers to the process of removing personnel off of standard and repetitive surveillance tasks and placing them on to tasks that require analysis, supervision and decision making. This change is particularly essential to the security personnel at MRTS because their performance depends rather on their ability to evaluate circumstances and make informed judgment than to spend hours of active observation [5]. Other scholars have noted the current challenge of properly identifying abnormal or suspicious passenger actions in surveillance images, especially where the identification has to occur in a short period of time to avert crimes or deal with incidents. Simultaneously, research on the implementation of artificial neural networks (ANN) in workforce scheduling demonstrates that intelligent planning systems are capable of considering multiple aspects of operations in a more efficient manner than manualized approaches. These systems are able to adjust to changing workloads, immediate operational needs and different levels of risk while planning workforce deployment [6]. The results indicate that the tools related to AI can be successfully applied to support adaptive staffing of security duties in MRTS operations, in particular, when the number of people to be hired depends on the increase in passenger movement and on a change in perception of the threat levels. Extensive research on Artificial Intelligence based video analysis shows that this type of system is able to perform better than the conventional rule based strategies in detecting suspicious behaviour in CCTV videos. [7]. These systems are capable of detecting complex spatio-temporal patterns, providing early warning signals of potential criminal activity or security incidents in time to issue alerts.

### *2.2 Challenges of Conventional CCTV Monitoring*

Traditional CCTV surveillance has been a critical component of the security management system of rail-based mass rapid transit systems. But the expanding size of urban transit systems and the volume of passengers have brought some drawbacks to conventional surveillance methods to light. Continuous monitoring of multiple camera feeds is one of the big challenges because of over-reliance on human operators. In large transit stations, security personnel are expected to monitor many screens at once for long periods of time, which can lead to fatigue, decreased concentration and slower detection of suspicious activity or emergency [8]. This constraint diminishes the effectiveness of traditional surveillance activities.

One of the other challenges is that Conventional CCTV systems lack intelligent real-time analytics. Conventional mechanism is primarily passive, relying on manual observation and inspection of recorded footage after the event. This can lead to incidents like theft, trespassing, crowd congestion and vandalism to go unnoticed, which can dslow the security response and increase the operational risk in the transit environment [9]. Conventional surveillance systems are further undermined by not being able to automatically identify anomalies or suspicious activity.

Besides, traditional CCTV monitoring adds to high manpower and operational expenses. Transit authorities are frequently called upon to have a lot of staff available for 24 hour monitoring throughout stations and rail corridors. This results in higher labour, supervision and workforce management costs and reduced efficiency [10]. These challenges have spurred the use of AI-driven surveillance and smart analytics solutions that can enhance monitoring precision and optimize security personnel allocation.

### *2.3 AI Based surveillance and crime detection*

The development of AI-powered surveillance has been mainly driven by advances in computer vision and deep learning technologies. The extensive research on Artificial Intelligence based video analysis makes this type of system capable of performing better than conventional rule-based strategies in detecting suspicious behaviour in CCTV videos. These systems can identify indications of potential criminal activity or security incidents early enough by identifying complicated spatial and temporal trends and can therefore send alerts in time. AI-based surveillance systems have been found to be more accurate in object identification and tracking even under challenging transport environments such as crowded areas, obstructed views and variable lighting. These systems operate on anomaly detecting models which learn the normal behavioral patterns and detect abnormal activities as they arise. The learning mechanism reduces the necessity of manual monitoring all the time and simplifies the process of monitoring what is happening at the stations and platforms. This is particularly applicable in MRTS systems where a huge number of individuals use the trains and could not have a huge number of individuals monitoring everything [11]. Meanwhile, other scientists cautioned that AI in security surveillance may render things less safe, as it is extremely dependent on a robust network connection and digital infrastructure, which may pose a threat to functionality. Simultaneously, they have developed specialized technologies, such as automated weapon detection devices, which can locate guns in surveillance video in real-time, which further extends the operational capabilities of AI-powered security operations [12].

### *2.4 Manpower planning and deployment*

Beyond aiding in the detection of security incidents, AI is also emerging as a tool to support planning and decision-making in managing security of the organization in a better way. Numerous organisations use AI powered systems to make duty rosters and deploy security workforce in a more efficient way. These systems review current surveillance data as well as historical data to determine hazards at various sites. According to this evaluation, AI tool assists in balancing the manpower available and the expected security needs, which result in improved coverage and improved resource utilization [13]. The artificial neural network scheduling model suggests that these methods might be useful to improve the effectiveness and efficiency of using security resources. This has introduced a new trend in the way that security is deployed, and uniformed security is being replaced by demand responsive and risk informed security. Rather than assigning equal numbers of people to all the stations, AI supported systems pay more attention to the areas and timeframes where the risk is greater. This approach has been deemed to be more efficient than traditional deployment of workforce especially in the public sector undertakings that are constrained by financial constraints. Simultaneously, researchers emphasise the necessity to tackle psychological and organisational issues associated with the introduction of AI. One of the most frequent issues that are encountered when implementing new technologies is employee resistance; that is, when the new technologies are viewed as threats to their work rather than as tools to help them do what they want. Therefore, it needs to be trained and conducted awareness programmes to ensure that its workers become confident in using advanced technological systems. It is also suggested that AI is altering the manner in which work is distributed among humans and machines. [14]. AI can be used to optimize the accuracy of operations and control workflows by automating routine monitoring activities, enabling deployed workforce to focus more on priority tasks such as making decisions, reacting quickly to incidents and overseeing operations. Consequently, human personnel will be able to focus on more judgmental tasks, as well as on situational knowledge and people interaction, whereas AI systems will cope with repetitive surveillance tasks, which will result in the overall greater performance of the security system. [15]. Previous research in the field of MRTS security has highlighted the importance of the high reliance on human surveillance of CCTV cameras and upon physical patrols. These kinds of arrangements are often linked to inefficiencies in operation, fatigue and slow responses by staff, particularly in transit networks with a high ridership. Recent studies have shown that newer surveillance systems supported by artificial intelligence, based on technologies such as computer vision and deep learning, are more effective in detecting unusual behaviour, intrusions and unattended objects and crowd density [16]. The use of these mechanisms will reduce manpower monitoring of the environment and improve consistency of threat detection. AI-powered surveillance can also be expected to reduce labor and operational expenses, as it automates the analysis of video streams, and reduce time spent reviewing videos and investigating incidents. Besides, centralized control rooms and alert based interfaces allow to have less monitoring staff on more areas. Overall, existing studies suggest that the use of AI in MRTS surveillance can bring about a more proactive and efficient approach, minimize human error, and improve the accuracy of detection and optimisation of manpower utilisation, potentially leading to more intelligent and efficient security management in the future.

### *2.5 Ethical, organisational and governance challenges*

The rapid advancement of technology has raised many organizational, ethical and governance questions about the emerging use of artificial intelligence based surveillance systems. Studies on employment and automation shows that the workforce opposes the innovations and is looked as threat to job security rather than as a supportive tool. This resistance to Artificial Intelligence based technologies can slow down adoption and ultimately reduce the potential benefits that AI powered technologies could offer in security survielliance. As a result, this can seriously affect the successful implementation of these technologies. [18].

Privacy and data protection issues are generally highlighted as part of AI powered surveillance discussions. Researchers stress to establish concrete systems of accountability, as well as to implement data security practices and enforce guidelines to collect, store and use surveillance data [19]. Confidence of passengers in the context of a public transport system is a factor that can be used to determine the social acceptability of surveillance measures. Surveillance may result in a lack of trust and legitimacy when it is overly monitored and lacks transparency about data use [20]. Thus, the successful deployment of AI-driven surveillance systems in MRTS is not only technologically sound but also requires appropriate ethical protection, effective information dissemination and effective institutional control.

### *2.6 Disaster resilience and MRTS relevance*

From a disaster management perspective, security failure in MRTS can quickly turn into mass casualty events, particularly in stations with high footfall and interconnection. AI-assisted surveillance has also been noted as an effective measure to mitigate disaster risk and detect hazards. These systems can detect sudden crowd movement, abnormal behaviour patterns and even early signs of operational pressure like bottlenecks or panic behaviour [21]. Recent researches on security surveillance make such systems a key component of urban infrastructure instead of being a mere security tool. Such critical importance is to help in disaster preparedness, responding in real time during an incident and post disaster analysis. By combining deep learning with sophisticated forecasting and scheduling systems, researchers show that AI-driven surveillance can streamline the process of workforce deployment and increase preparedness troublemaking scenarios, thus increasing institutional capacity to process contingency plans [22]. The security surveillance and workforce distribution with the aid of artificial intelligence (MRTS) is considered a critical element in improving security and disaster management. Empirical studies establish the fact that smart surveillance systems can detect suspicious acts like explosion, violence and armed unrests. Early detection of such incidents helps in timely intervention and coordination of response systems among security agencies [23]. Further studies on video surveillance based on machine learning and deep learning algorithms have also found key issues for practical implementation. Topics such as uneven data, variations in environmental conditions and difficulties of incorporating new technologies into existing systems. Such issues need to be addressed in order to successfully integrate such surveillance tools into operational settings [24].

## 3. Research methodology

Quantitative cum deductive research approach is used to analysis the secondary data to understand the existing patterns of manpower deployment in CCTV based surveillance and to assess the potential of AI powered surveillance technologies as a more efficient alternative. A systematic review of peer reviewed journal articles, conference papers and institutional publications on artificial intelligence in surveillance, manpower planning and security automation was conducted to form the conceptual foundation of the research. Secondary data were drawn from reliable and publicly accessible sources, including official information released from the Press Information Bureau (Government of India), operational information from the Delhi Metro Rail Corporation (Mobile Application, Website, Official Social media updates, etc.) and reports published in major national newspapers. This quantitative cum deductive approach is used to frame a conceptual framework of optimized manpower deployment in security surveillance operations based on the synthesis of the reviewed literature and obtained data that is aimed at a rapid response to incidents, cost-effectiveness, manpower planning and minimization of operator fatigue. Deductive approach allows the researcher to base the conceptual framework on the capabilities of artificial intelligence such as body posture, skeletal motion, face recognition and auto alert generation when unauthorized persons enter restricted areas, enabling it to be more active and reactive to security control. Researcher uses the quantitative estimate of manpower requirement and associated cost to justify the conceptual framework. These quantitative estimates are based on the deployment data of stations in Delhi Metro Rail Corporation and enable a systematic comparison between the current system of manpower-intensive CCTV monitoring and the suggested AI powered surveillance model at both current and upcoming stages of Delhi Metro Rail Corporation.

## 4. Case study: Delhi Metro Rail Corporation (DMRC)

The Delhi Metro Rail Corporation is the largest and one of the busiest Mass Rapid Transit Systems (MRTS) in India, serving millions of passengers daily through an extensive network across the Delhi–National Capital Region (NCR). As India's largest metro rail operator, DMRC plays a crucial role in urban mobility and offers an important context for examining passenger movement and transit challenges. According to official statistics, the corporation recorded about 235.8 crore passenger journeys in 2025, with an average daily ridership of approximately 64.60 lakh commuters, reflecting both the scale and significance of its operations [25]. With the ever expanding metro network, the scale and complexity of security management has increased proportionally. There is a strong need for more efficient and technology driven surveillance mechanism. Reliance on traditional security arrangements that depend primarily on manual monitoring places a great burden on manpower resources. In this sense, the use of artificial intelligence based surveillance systems offers great potential for improving passenger safety, enabling more efficient crowd management, facilitating faster responses to emergencies and simultaneously reducing the total operating costs for the deployment of security personnel.

### *4.1 Present security scenario*

The existing security arrangement of Delhi Metro Rail Corporation (DMRC) is mainly supported by workforce from the Central Industrial Security Force (CISF), with additional assistance from private security agencies and DMRC's internal staff. Information released by the Press Information Bureau and DMRC indicates that by 2021 the metro network had deployed over 14,000 security staff. Their primary responsibilities revolve around monitoring CCTV feeds, patrolling station premises including essential buildings, conducting luggage and baggage screening at station entry points, responding to alarms and observing any suspicious behavior [26]. As the operational network of DMRC has 256 metro stations in Phase III and 15 metro stations in Phase IV, it is rather difficult to control the movement of people and have a comprehensive security coverage. Electronic surveillance security staffs are usually fatigued and as a result, their concentration and visual awareness decrease during working hours. The mental load is too heavy when one operator has to view sixteen or more video feeds at a time on large monitoring screens. Consequently, this makes the process of detecting possible threats in real time inconsistent and unreliable [27]. One of the major disadvantages of manual surveillance systems is the delay that is generally experienced in responding to emergencies. In the present set-up, it may take time for security personnel to respond effectively to issues such as theft, unauthorised access to tracks or unattended baggage or conflicts amongst passengers.

### *4.2 Benefits of AI based surveillance in DMRC*

Replacing conventional CCTV surveillance with AI-driven surveillance systems with data analytics is a core upgrade to the security infrastructure of DMRC. These AI enabled hardware and software can be used to detect faces, unusual behavior, unattended or suspicious objects and can analyze body posture and movement patterns and alert authorities when unauthorized individuals are detected in restricted zones. All these functions are capable of working in real-time and with no constant human control and enhancing the overall efficiency of security monitoring.

The AI driven surveillance systems linked with the DMRC operational control center can operate based on real time data analysis. These systems can implement different algorithms for definite security tasks. For example, object detection can be executed using YOLO (You Only Look Once) models, while behavior pattern analysis over time can be conducted through Long Short-Term Memory (LSTM) networks. Crowd density estimation can be done using convolutional neural network based methods. During peak hours of journeys when footfall increases, the system can automatically notify the station controllers so that the crowd control measures can be put in place at the earliest. In the baggage monitoring, the AI mechanism can decide whether an item has been left temporarily or unattended by monitoring the time it remains at a location. Such alerts can be linked with Passenger Information Display Systems (PIDS) and bulk SMS communication systems that could be used to automatically make announcements, send messages to mobile control teams and trigger predefined emergency response procedures.

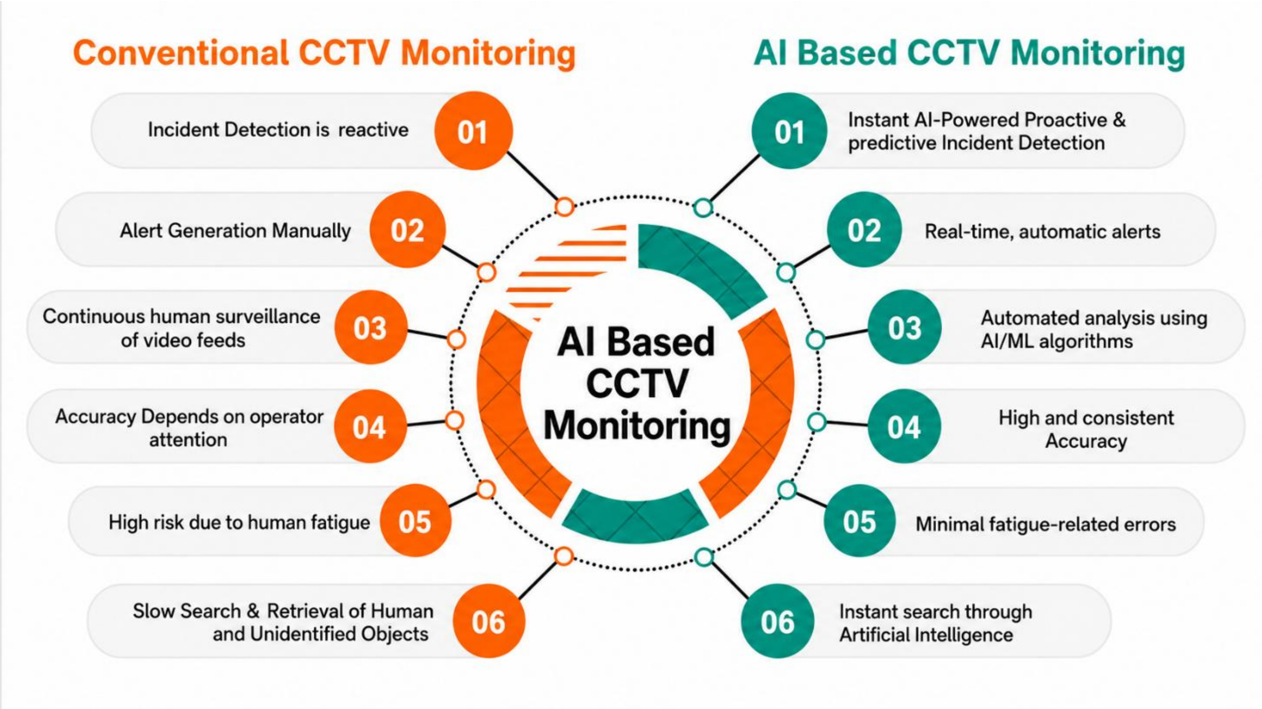


**Figure 1: Advantages of AI powered monitoring over Traditional CCTV monitoring**

Analysing behaviour using artificial power also helps identify passengers who may be in distress. The system is capable of detecting abnormal actions or emotional signals such as anxiety, aggressive behaviour, continuous crying or erratic movements. In such cases, a caution alarm can be immediately notified to the security control room for quick response by field staff. This function is especially helpful in preventing such incidents as suicide attempts on metro tracks. This way, AI-supported surveillance can improve security and, at the same time, contribute to public safety and fast help for those suffering from emotional or psychological hardship.

Furthermore, surveillance technologies based on artificial intelligence are especially appropriate for the detection of trespassing and monitoring of unauthorised movement in rail corridors, particularly in sections without the installation of platform screen doors. These systems can automatically detect an entry into restricted track areas, accidental or intentional. They can also detect activities such as cable theft and send alerts to the relevant staff for immediate action [28]. Artificial intelligence application in surveillance allows to timely detect unusual events and take preventive actions, which increases operational safety and reduces the possibility of accidents on tracks and damage of infrastructure. Unlike human operators, AI powered systems can monitor hundreds of video channels at the same time and analyse the visual in real time. This enables metro authorities to react quickly to situations such as unattended baggage, passenger separation, abnormal crowd behaviour and security breaches. The ability to continuously monitor on a large scale with consistent performance clearly provides an operational advantage over conventional security surveillance approaches

### *4.3 Scalability of AI/ML Based Surveillance*

One big plus of AI driven surveillance versus traditional human monitoring is that it scales up easily. Traditional surveillance involves periodic hiring, training, deploying and supervising staff which is time consuming and has recurring expenditure. On the other hand, AI surveillance systems require a large upfront investment in technology and infrastructure. After installation, the system can be extended step-by-step by adding more cameras or processing nodes without a corresponding increase in labour. Centralised monitoring dashboards enable metro authorities to monitor activities across multiple stations from a single control center, thereby making network wide management more efficient and economically sustainable.

This expansion capacity becomes more important in the light of DMRC's future growth plans. Phase V (A) of the Delhi Metro project has been approved by the Government of India. By the year 2031, the total number of metro stations will go up to 352. With the growth of the network, the security management will be very difficult with conventional surveillance. In this context, scalable technological mechanisms such as AI powered surveillance systems can reinforce efficient monitoring across a bigger network without requiring a proportional increase in workforce [29].

As the number of DMRC stations are growing, it is important to consider the past incident records and passenger movement data while planning for security deployment. AI powered solutions can help identify vulnerable locations & time periods when risks are higher and areas where incidents are frequent supported by data analysis. This will allow management to deploy security staff at identified location instead of allotting staff equally across all stations. Such a data based and risk focused approach can improve operational efficiency, ensures optimized manpower deployment and will support in maintaining strong public safety standards across a growing and more complex metro network.

## 5. Data collection and analysis

### *5.1 Data sources and collection approach*

This research is of a quantitative research type, using secondary data to develop a framework for manpower deployment in CCTV monitoring in conventional surveillance systems. It also considers the potential benefits of transitioning to AI-assisted surveillance techniques. Secondary data have been used for ensuring objectivity and reliability and making the study practical. This is an appropriate approach, as the study is focused on security practices in a large urban transit system, not individual behavioural responses.

The data used for this study was obtained through different credible sources that concerned MRTS and urban security. The Press Information Bureau (PIB) reports of the Government of India, data about the operations of the Delhi Metro Rail Corporation (DMRC) and reports of major national news agencies were the main sources of data. These sources were helpful in giving information about the infrastructure of surveillance, deployment of security officers, application of technology and operational issues in the metro rail systems. To be sure of accuracy and consistency of the data, only authentic and reliable sources were chosen. The gathered information was analyzed, filtered and organized in a systematic way such that a clear comparison can be drawn between the traditional CCTV surveillance systems and AI based surveillance systems such that there are clarity and transparency in the analysis.

### *5.2 Baseline manpower estimation*

This paper has used the manpower analysis on the CISF deployment data of the Phase III operating network of DMRC. Based on the data provided in Table 2, there are 14000 CISF personnel spread out on 256 metro stations with an average of approximately 54.69 security personnel per station daily. This figure also adds personnel that work in other operational and support units like leave reserves, weekly rest, training duties, quick response teams, dog squads, patrolling units, bomb disposal squads and clerical works. The overall workforce figures need to be adjusted by taking into account staff allocated to these other duties to come up with a realistic estimate of the number of personnel who can be assigned to active operational duties.

**Table 2: Average security workforce deployed by CISF up to phase III (Source:** Press Information Bureau, Government of India; DMRC Reports)

| Parameter | Value |
|---|---|
| Total CISF staff deployed | 14000 |
| No. of Stations (Phase III) | 256 |
| Average Security Manpower per Station per Day | 54.6875 |

### *5.3 Projected manpower requirements*

Future manpower requirements were estimated by multiplying the number of stations in each upcoming phase with the average number of personnel required per station, based on the baseline values shown in Table 2. This method helps ensure that the projections are grounded in existing deployment patterns and reflect realistic operational conditions as the metro network continues to expand.

**Table 3: Security Manpower Estimates for Different Operational Phases** (Source: Author's compilation based on collected quantitative data)

| Parameter | Up to Phase III | Up to Phase IV (Priority Corridor) | Up to Phase IV (Remaining Corridor) | Up to Phase V(A) |
|---|---|---|---|---|
| Target Date | January 2026 | January 2027 | January 2030 | January 2032 |
| Projected CISF Manpower | 14000 | 16406 | 18539 | 19250 |
| No. of Stations | 256 | 300 | 339 | 352 |

A review of manpower deployment records indicates that nearly 9% of the total security staff is assigned only to CCTV monitoring duties. This finding indicates that continuous video surveillance requires a considerable amount of manpower in MRTS security operations. It also outlines that this area has strong potential for improvement, where the use of AI based surveillance could help reduce manpower requirements and improve operational efficiency.

**Table 4: Security Manpower Estimates for Different Operational Phases** (Source: Author's compilation based on collected quantitative data)

| Security Function | Estimated Share of Total Deployment | Functional Role in Current System | AI Automation Potential |
|---|---|---|---|
| Access control and baggage screening | 30-40% | Screening at station entry points through X-ray systems, door frame metal detectors, frisking support and passenger regulation | Partial |
| Platform patrolling and crowd management | 25–30% | Platform supervision, visible presence, crowd regulation, passenger guidance and immediate physical intervention | Low |
| Dedicated CCTV monitoring | 8-9 % | Monitoring surveillance feeds in station control rooms and centralized control settings, observing incidents and communicating alerts | **High** |
| Quick Response Teams (QRT) | 7–9% | Mobile response to suspicious activity, emergencies and escalated incidents | Low |
| Train escort duties | 7–9% | Escorting trains on selected routes and addressing onboard disturbances | Low |
| Dog squads and bomb disposal units | 4-5% | Specialist explosive detection and high-risk security response | Low |

| | | | |
|---|---|---|---|
| Administrative, reserve, and training support | About 10% | Coordination, reserve strength, relief arrangements, training and institutional support | Partial |

## *5.4 CCTV specific manpower projection*

Using the 9% manpower share identified earlier, Table 4 shows rank-wise estimates of the personnel required for CCTV monitoring in both the present and upcoming phases of DMRC. The table also indicates the additional staff that would be needed at each phase as the metro network expands.

**Table 5: Rank-wise projected manpower dedicated to traditional CCTV monitoring** (Source: Author's compilation based on collected quantitative data)

| **Rank** | **Phase III (9%)** | **Phase IV Priority (Additional)** | **Phase IV Remaining Corridor (Additional)** | **Phase V(A) (Additional)** | **Overall Total** |
|---|---|---|---|---|---|
| Constable | 579.60 | 99.62 | 88.30 | 29.43 | 797.0 |
| Head Constable | 548.10 | 94.20 | 83.50 | 27.83 | 753.6 |
| Asst. Sub Inspector | 25.20 | 4.33 | 3.84 | 1.28 | 34.7 |
| Sub Inspector | 100.80 | 17.33 | 15.36 | 5.12 | 138.6 |
| Inspector | 6.30 | 1.08 | 0.96 | 0.32 | 8.7 |
| **Total** | **1,260.00** | **216.56** | **191.95** | **63.98** | **1732.5** |

The projections reveals that adopting AI based surveillance could optimize the manpower of 1733 staff having duties of CCTV monitoring across the operational and sanctioned DMRC network. These personnel could instead be reassigned to more critical field level security duties, improving the overall effectiveness of security operations.

## *5.5 Cost projection framework*

Future manpower expenses were estimated based on the expected implementation of the Revised Pay Scales of Government of India, which is due from 01 April 2026. For this estimation, a tentative fitment factor of 3.0 was applied, following the general approach adopted in previous pay commissions. Using this assumption, revised salary levels were projected for different ranks. Table 5 shows the rank-wise annual cost to company (CTC) calculated under both the Seventh Pay Commission and the projected structure of the Eighth Pay Commission**.**

**Table 6:** Rank-wise Annual CTC under Existing and Proposed Pay Scales (Source: Author's compilation. 8th CPC estimates based on tentative fitment factor of 3.0; subject to official notification.)

| **Rank** | **Pay Level** | **Annual CTC (in INR)** **(as per existing Pay-scale)** | **Projected Annual CTC (in INR)** **(As per expected Pay-scale)** |
|---|---|---|---|
| Constable | Level 3 | 0.60 Million | 0.97 Million |
| Head Constable | Level 4 | 0.72 Million | 1.14 Million |
| Asst. Sub Inspector | Level 5 | 0.84 Million | 1.27 Million |
| Sub Inspector | Level 6 | 1.08 Million | 1.62 Million |
| Inspector | Level 7 | 1.32 Million | 2.10 Million |

The cost estimates in the study consider only salary expenses, as salary forms the main and most measurable part of manpower costs. Other types of expenditure that normally arise in actual deployment have not been included in these calculations. These may involve costs related to insurance, medical support, weapons and equipment, uniforms, accommodation and canteen facilities. Therefore, the total financial burden associated with security manpower deployment in practice is likely to be higher than the figures presented in this analysis.

## *5.6 Ten-Year cost projection for conventional CCTV monitoring*

Using the salary figures shown in Table 5, the cumulative manpower expenditure related to conventional CCTV monitoring was projected up to the year 2035. The calculation takes into account the gradual expansion of the metro network in phased manner, with costs estimated separately for each operational phase according to the number of years it is expected to function before 2035.

**Table 7:** Projected Cost of Conventional CCTV Monitoring (2026 to 2035) (Source: Author's compilation. *Based on proposed pay scales; other operational costs excluded.)

| **Phase Commencement** | **No. of Stations** | **No. of Staff (CCTV)** | **Annual Salary Cost (Million)** | **Years Until 2035** | **Total Cost by 2035 (Million)** |
|---|---|---|---|---|---|
| Jan-2026 (Operational) | 256 | 1260.00 | 880.74 | 1 | 880.74 |
| Jan-2027 (partially operational) | 300 | 1476.56 | 1636.86 | 9 | 14731.72 |
| Jan 2030 (Projected) | 339 | 1668.52 | 212.79 | 6 | 1276.75 |
| Jan 2032 (Projected) | 352 | 1732.50 | 70.93 | 4 | 283.72 |
| **Overall Total** | | | | | **17172.93 INR** |

According to estimates, if conventional methods for monitoring CCTV are used until 2035 without any use of artificial intelligence (AI), then the total salary spent for CCTV only surveillance personnel will be approximately. This large cost highlights the financial advantage of moving towards AI-powered surveillance systems. Unlike the traditional model that requires continuous spending on manpower, AI based systems mainly involve an initial one-time capital investment in technology and involve much lower recurring manpower costs over time.

## *5.7 Manpower Mapping and Resource Deployment*

The changeover from traditional to AI-based surveillance indicates a paradigm shift in the security manpower deployment strategy of rail based MRTS. The conventional model, upto Phase III Operational Stations, deploys 1,260 dedicated monitoring staff to monitor about 14,600 station-based cameras. Under this manual regime each operator is responsible for roughly 16 cameras at any one time, a density that exceeds the established cognitive limits for effective vigilance by a factor of 3 to 4. Evidence shows that human vigilance deteriorates considerably after 10-20 minutes of passive observation, making the traditional mode of detection reactive with latencies of minutes.

The proposed AI powered surveillance model also utilises the existing hardware infrastructure but restructures the oversight hierarchy at a fundamental level. Transitioning to alert-response mode reduces the number of needed monitoring personnel to about 126 AI supervisors for Phase III Operational Stations, a 90% reduction in sedentary monitoring roles. That means one supervisor can now effectively control 116 cameras – a tenfold increase in the span of control – because the AI takes over the key task of continuous scanning, 24/7. The most important outcome of this mapping is the proactive detection ability that significantly reduces the alert latency from minutes to seconds. Furthermore, about 1,134 personnel can be shifted from passive observation to high impact field roles for stations of Phase III and then for proportional for future extensions. This shift from reactive, after-the-fact, to proactive and before-the-fact means security resources are concentrated where they are most useful: on the ground and not behind a screen.

**Table 8:** Mapping of Manpower based on Conventional and AI powered Monitoring (Source: Author's compilation)

| Parameter | Conventional Monitoring | AI-Powered Monitoring |
|---|---|---|
| Dedicated monitoring staff (Phase III) | 1,260 | ~126 AI supervisors (est.) |
| Effective vigilance per operator | 10-20 min (cognitive limit) | Continuous -- 24/7 |
| Alert detection latency | Minutes (reactive) | Seconds (real-time) |
| Detection mode | Passive -- post-event onset | Proactive -- pre-onset flagging |
| Estimated personnel available for redeployment | — | ~1,134 field roles |

## 6. Results

The paper presents framework for planning the manpower in MRTS considering operational requirements with specific functional roles in the operational network and projected phases. The study found that nearly 9 per cent of the Central Industrial Security Force personnel working for the Delhi Metro Rail Corporation are just there to watch regular CCTV systems. By the time of Phase III operations, with the baseline deployment of around 14000 security staff at 256 metro stations, this means that around 1260 personnel are currently engaged only in manual observation of video surveillance feeds upto phase III stations. The manpower estimated for traditional monitoring only is when projections are extrapolated to all approved expansion stages of Delhi Metro Rail Corporation, i.e. Phase IV (Priority), Phase IV (Remaining) and Phase V (A).

A rank-wise analysis shows that most of the workforce deployed for CCTV monitoring duties are Constables and Head Constables. This shows the human dependence for traditional monitoring systems mechanism, as they require people to continuously monitor and interpret the surveillance footage. The analysis further states that the required personnel to provide traditional CCTV Monitoring will also increase at a similar level under the extension of Delhi Metro Rail Corporation's network from around 256 to 352 Stations. This will increase both the cost and the number of staff needed, but it won't make it any easier to find threats. Figure 2 shows the relation between growing number of metro stations and the rising costs of security staff salaries. This clearly shows indicates the traditional way of doing surveillance is putting more and more strain on the budget.

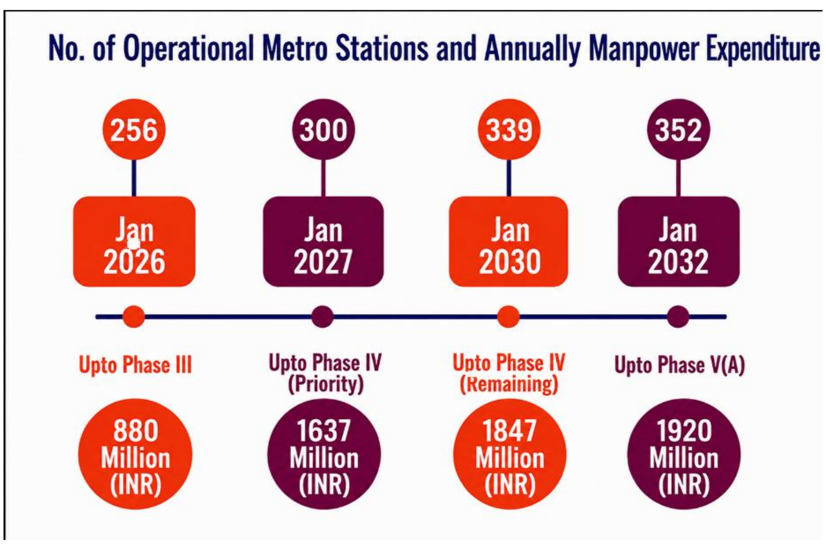


**Figure 2: Number of Metro Stations and Corresponding Salary Expenditure on Deployed Security Staff**

## 7. Discussion

The results of this study reveal structural inefficiency in the conventional CCTV monitoring system being implemented in rail based MRTS system. Allocating nearly 9% of total security manpower to routine passive video monitoring, a task that AI based systems can carry out with greater consistency, faster processing and wider coverage, continuing to rely on conventional monitoring creates considerable and unnecessary operational cost. Findings reveals that adopting AI powered surveillance could reduce the need for around 1560 dedicated CCTV monitoring staff across the sanctioned network of DMRC, leading to cumulative salary savings of approx. 17172.93 million INR between 2026 to 2036. Out the projected 1733 CISF personnel in conventional CCTV monitoring upto Phase V(A) stations, approximately 173 would be retained as AI supervisors, making net savings of 15,455.64 million INR. The remaining 1466 personnel become available for redeployment to active field security roles: strengthening platform patrolling density, reinforcing Quick Response Team coverage, or absorbing Phase IV and Phase V field expansion. AI-based surveillance systems are capable of simultaneously observing hundreds of video streams, recognising the unusual activities in real time and automatic generating alerts, can effectively replace the conventional monitoring function which is required to be performed by 1733 security staff across the DMRC network, With the use of AI technology, many of these staff members could instead be reassigned to duties that require human judgment, such as field response, threat mitigation and assisting passenger. The shift to AI powered surveillance is not only cost effective but also improves disaster preparedness and operational stability in Mass Rapid Transit Systems. As established in the literature, AI tools equipped with crowd density analysis, behavior monitoring and real-time alert systems can identify the early indicators of emergencies such as crowd build ups, identifying distress passengers or unauthorised track access faster and more reliably than manual monitoring, causing fatigue during long observing periods. Identification of early-stage risk is a vital measure to lessen the potential disasters in high footfall stations of Delhi Metro Rail Corporation where a small incident can escalate into a serious emergency.

### *7.1 International Evidence: Validated Operational Benchmarks*

Before making the case for DMRC specifically, it is worth establishing that the proposition being argued that AI Powered surveillance outperforms human monitoring in mass transit environments is not theoretical. Table 8 presents the evidence

**Table 9:** International Metro AI Surveillance Deployments -- Comparative Operational Evidence (Source: Author’s compilation)

| Metro System | Deployment | Key Capabilities | Measured Outcome | Relevance to DMRC |
|---|---|---|---|---|
| Transport for London Smart Stations Pilot (2022-2023) | 11 AI algorithms applied to 24 existing cameras at Willesden Green station; alerts delivered to staff via mobile device | Aggressive behaviour, weapon detection, fare evasion, track falls, platform-edge proximity | 44,000+ total alerts; 19,000 delivered in real time to frontline staff | High. Proves AI works on existing cameras without hardware replacement -- directly applicable to DMRC's 14,600 Phase III cameras. Human staff act on alerts; cognitive load removed. Pillar I & III |
| SMRT Singapore iSafe System, Bukit Panjang LRT (2022-2023) | Edge-based AI analytics on 104 cameras across 13 driverless stations; real-time alert pipeline to OCC | Track intrusion detection; unauthorized zone entry; real-time OCC alerts | 99.8% intrusion detection rate; completed ahead of schedule; LTA Safety and Security Award 2023 | Very High. Singapore's dense driverless system mirrors DMRC's UTO lines (Lines 7 and 8). Track intrusion alerts are the single most direct disaster-prevention application for DMRC's open-track |

| | | | | |
|---|---|---|---|---|
| | | | | sections. Pillar I & III |
| Dubai Metro (RTA) AI Crowd Management (ongoing) | Real-time crowd density analysis and prediction; proactive station redistribution during peak events | Crowd density monitoring; congestion prediction; automated flow management | Congestion reduced 40-60% during peak events and major public gatherings | High. Dubai's peak-event challenge mirrors DMRC's daily peak-hour footfall (6M+ commuters). 40-60% congestion reduction translates directly into crowd-surge prevention - the most common disaster scenario in Indian metro systems. Pillar II & III |

The discussion should also recognise the practical limitations and challenges in shifting to AI-supported surveillance. First, the price of acquiring AI system, installation, integration with the current network and maintenance of the related software has not been estimated in this paper and it would be a considerable initial investment. Before full scale deployment decisions are made, a cost benefit analysis of the implementation costs of AI versus manpower savings in a specified recovery period is required. Moreover, the transition can pose organizational and labor force issues. Structured capacity building programs should provide security personal with proper training and redeployment opportunities in order to ensure that institutional acceptance and continuity of operations remain intact should their current responsibilities come into play. Moreover, the implementation of AI surveillance in transportation also poses relevant ethical and governance concerns, such as the privacy of passengers, safe processing of data, facial recognition technology and responsibility in the automated decision-making. These issues should be overcome by providing explicit regulatory Framework prior to such systems being rolled out on a big scale in MRTS network.

There are also some limitations to note on the data that was used in this study. The estimates of the manpower are informed by the data published by the Press Information Bureau in 2021, and the current levels of deployment might be different. The research that approximately 9 percent of the security personnel are allocated to CCTV surveillance is based on the secondary sources and is not verified by the primary data available directly with the Central Industrial Security Force (CISF) or the Delhi Metro Rail Corporation (DMRC). Moreover, the calculations of the costs are made by assuming a fitment factor of 3.0 as per the proposed Pay Revision, and this could vary after the official notification is announced. Due to these, the estimates made in this study have some degree of uncertainty. This limitation can be overcome through future studies that use field surveys and institutional data that has been verified.

## 8. Conclusion

This study undertakes the Delhi Metro Rail Corporation as a case study to look at the cost outcomes of traditional CCTV-based monitoring. Analysis and observation conclude that manual CCTV monitoring is expensive, exhausting for staff, and simply won't work as the network keeps growing. For security surveillance DMRC will need to deploy 1733 security personnel dedicated solely to manual CCTV surveillance for stations upto Phase V(A), following current technique of Conventional Monitoring. Over a period of ten years, this activity alone is estimated to cost about 17172.93 million INR. Beyond the money, it has a mental toll on employees who need to stay perfectly alert while staring at endless video feeds for hours. Since AI-powered surveillance systems can automatically analyze video streams, this task can be managed more efficiently with technology while also lowering recurring operational costs. AI assisted surveillance has definite benefits in various operational levels. These include improved accuracy in identifying suspicious activities, less mental strain on deployed staff monitoring surveillance cameras, fast response to emergencies and the ability to monitor large areas without requiring a similar increasing the manpower. Importantly, the systems are capable of disaster preparedness by identifying abnormal crowd movement, identifying passengers in distress and security breach at the early phase, which places AI based monitoring as a part of MRTS infrastructure and not just a security management tool, but as an essential tool.

The proposed deployment framework encourages a strategic shift in security operations within Mass Rapid Transit Systems (MRTS) security operations. Under this approach, human personnel would gradually move away from from passive monitoring roles to active and focus more on roles that require judgment, decision-making and instant response. At the same time, AI based systems would manage high volume surveillance activities. For this purpose, a holistic approach will be required in acquiring technological investments in AI technology, workforce reskilling & training and the formulation of clear ethical policies & governance frameworks to ensure the responsible and socially acceptable deployment of AI based surveillance systems.

## 9. Future perspectives and recommended research

Since it is the beginning of the integration of AI-powered surveillance in metro and rail networks, there is a clear and pressing need to research and innovate further for the real-world impact. In future research, it is suggested to conduct a cost-benefit analysis in order to assess the effect of adding AI powered surveillance to Rail based Mass Rapid Transit Systems (MRTS). This would take into account all costs – not just the sticker price of hardware but about getting the full financial picture from the initial investment in equipment and the technical challenge of merging it with existing systems, to the ongoing costs of software licensing and maintenance.

A phased pilot approach is likely the best way forward to make this transition smooth and successful. AI and machine learning tools can be initially deployed at a limited number of stations of DMRC network having high ridership in phased manner before being scaled up across the complete operational network. Such pilot projects would provide empirical performance data especially related to false alarm rates, accuracy detection and operational impact under real transit conditions. The results would help to improve algorithms and operational procedures before large scale implementation. gradual scaling supported by continuous learning of models and regular validation can ensure both technical reliability and organisational sustainability of the AI supported surveillance framework in long run.

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