# Back on Track – A Review into Using AI to Mitigate Railway Disruption in the UK

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## 1. Introduction

### *Background*

The UK railway is a vital part of the nation's transportation infrastructure, connecting cities, enabling commerce and reducing reliance on cars. The Office of Rail and Road (ORR; 2023) reported that the UK Railway Network handles 1,385 million passengers and makes 17 billion tonne kilograms of freight transportation each year (Department for Transport, 2021).

The impact of delays can be felt at various levels, from passenger dissatisfaction/safety to the disruption of business and the wider economy. Delays can also increase carbon emissions and waste energy. This highlights the importance of improving rail services and using Artificial Intelligence (AI) as a tool for a more efficient and reliable network.

### *Key Themes*

In an initial search, we have noticed key trends and organised them into three key categories for rail delays: infrastructural/technical issues, natural factors and human error. Infrastructural and technical issues can consist of point and signal failures. Signal failures occur when train traffic lights stop working, halting operations and creating ripple-effect delays. Point failures happen when track switches break or get stuck, preventing trains from moving to the correct tracks. In 2023/24, the ORR reported that delays due to these issues had peaked, being the cause of 26% of cancellations across the network, (New Civil Engineer, 2024).

Also, weather can contribute to rail delays. While it can be a direct cause, it also can affect maintenance work and accidents which have an indirect impact on delays. Climate change has been found to increase damage to infrastructure through extreme weather events, such as buckling railway lines due to heatwaves (Ferranti et al., 2016). Leaves may fall on the tracks, causing a loss of wheel contact with the track and impacting train braking. A study by Garmabaki et al (2021) assessed the impact of different weather events on railway infrastructure through survey data. Heavy rainfall had a significant impact on railway operations, causing soil erosion and increased water flow around tracks, leading to slow services and cancellations. Finally, Ludvigsen and Klaeboe (2014) looked at the impact of heavy snowfall on rail delays, focusing on the weather events in 2010 in Norway, Sweden, Switzerland, and Poland. They aimed to evaluate how this extreme weather affected rail freight and assessed management responses. Findings revealed that snowfall exceeding 5 mm caused major delays of 3 hours on average.

Our final focus is the impact of human error on train delays. We classified Human Error into two categories: Train Dispatch Procedures (TDPs) and On Track Congestion (OTC). TDPs refer to overcrowding of platforms which will increase the loading time onto trains and delay departure, especially at busy commuter times with 1,774,400 daily passengers arriving into major cities across the UK (Department for Transport, 2023). OTC can be caused by poor decisions by operators and passengers, missing signalling, and incorrect scheduling. With TDPs and OTC come further challenges. Rescheduling is more frequent when rail traffic is near capacity (Corman et al 2017). Furthermore, Minbashi et al. (2021) identified that when there are a high number of arriving trains to a station, the yard operator becomes occupied with managing the incoming trains, leading to delays.

### *Significance of Review*

These delays put more pressure on other transport systems and increase road traffic. With increased pressure on the UK railway network, AI is becoming progressively meaningful to improve the system.

After establishing our key themes, we explored studies from many different countries that have focused on the use of AI to improve delay prediction and enhance the overall network. Looking outside of the UK allows us to take important findings and ultimately see if it is possible to implement them in our home system.

### *Initial Research*

The use of an acoustic-based system with deep learning was explored on Pakistan railways to detect track faults (Hashmi et al, 2022). They established an error with how track faults were detected and proposed a new way of combining traditional acoustic detection with two convolutional neural networks (CNNs), a recurrent neural network (RNN) and a long short-term memory (LSTM) model. The dataset was trained and tested on each of these models, and the LSTM model produced the most accurate detection with the least training. With extreme weather events in Pakistan causing track damage, this quick and efficient approach using a microphone can provide effective detection and improved railway quality and overall delays.

Automated Intelligent Video Review has been used by One Big Circle (2021), a UK-based tech company, and adopted by Network Rail in 2020. They use forward facing videos and thermal detection to spot anomalies and events that would often be missed if being reviewed manually. This technology detects thermal hot spots, track componentry, signal and lineside assets, offering real-time data of track conditions to predict accurate forecasts and identify patterns. They use machine learning models to capture defaults along railway tracks to identify whether intervention is needed. Combining this with expertise of engineers enables speedy diagnosis of problems and solutions to keep trains running, consequently reducing delays with services.

Furthermore, several studies have looked at predictive models to improve railway services. Li et al (2024) viewed stations and trains as different nodes and suggested that current models couldn't predict delays between these nodes. They introduced a SAGE-Het model to overcome this by connecting the nodes by edges (running times) and capturing their interactions. Using existing data on two parts of the China railway network, SAGE-Het outperformed existing prediction models.

Predictive models, especially in rail temperature forecasting, have made big strides. Models like CLF-Net and CNU RTPM show how newer technologies can beat the old methods, improving both accuracy and safety. The CNU RTPM model, introduced by Hong, Park, and Cho (2021), focuses on predicting rail temperatures using Extreme Gradient Boosting (XGBoost), a supervised machine learning decision-tree based technique. It takes in weather and solar data, like air temperature, wind speed, and solar irradiance, to make its predictions. The model also works with the Train-Speed-Limit Alarm-Map system (TSLAM), helping to identify high-risk areas and boosting both safety and efficiency in operations.

XGBoost has also been used in response to difficulties with human error on train services. Shafique (2024) used XGBoost to predict delays up to five days in advance on train lines in Australia. They used openly published occupancy data from 2018 - 2019, station data (entry and exit data), and weather data. Train lines that showed low occupancy were removed from the dataset. By putting this data into output categories, XGBoost was able to predict occupancy levels and concluded that the main factor impacting delays in this case was passenger overcrowding at stations.

A paper by Agasucci et al. (2023) highlighted problems with TDPs relating to difficult decisions made by traffic controllers. There are several constraints that these controllers base their decisions on such as signalling, infrastructure capacity and business rules. The authors noted that the traffic controllers have a limited perception of certain situations, making it hard for efficient decisions to be made, therefore they proposed some machine learning techniques. Two Deep Q-Learning methods were investigated on US railway data: centralised and decentralised. The centralised algorithm 'knows' the availability of all resources for the whole network taken from a single database and was used to plan the train route. It helped to predict future conflict and learn behaviours of the train network. The decentralised algorithm checked resource availability with a limited view of the network by assessing each node (station) individually. The centralised approach performed better for predicting dispatch delays and issues with the train route. It was also more scalable in terms of the railway network size.

This literature review will explore a range of AI-based approaches to mitigating rail disruption. Within these topics, we discuss Convolutional LSTM (Conv-LSTM), Gated Recurrent Unit (GRU), Convolutional Neural Networks (CNNs), CLF-Net, Barzilai-Borwein Incremental Grey Polynomial Regression (BBI-GPR) and Chungnam National University Rail Temperature Prediction model (CNU RTPM) and their ability to predict and mitigate rail delays.

## 2. Literature Review Method

Our literature search period spanned October to November 2024. We chose only journal articles for our final evaluation in order to focus on peer-reviewed research. Initially, we used the UK's *National Rail* website to establish our knowledge in the subject area and understand the current AI systems in place across the country. *The Office of Rail and Road (ORR)*, *KORAIL* and *CEIC* also provided important contextual data for our introduction. We focused our search exclusively on papers published during or following 2020. In the first quarter of 2020, the number of scheduled trains in the UK dropped more than 30% compared to the previous quarter (Figure 2.1) (Office of Rail and Road, 2024). This was due to the impact of COVID-19, limiting passengers to only essential travel. Since demand for the UK railways has returned to pre-pandemic levels, but scheduled train services are yet to fully recover. This puts extra strain on the railway network and directly impacts the likelihood of congestion and delays.

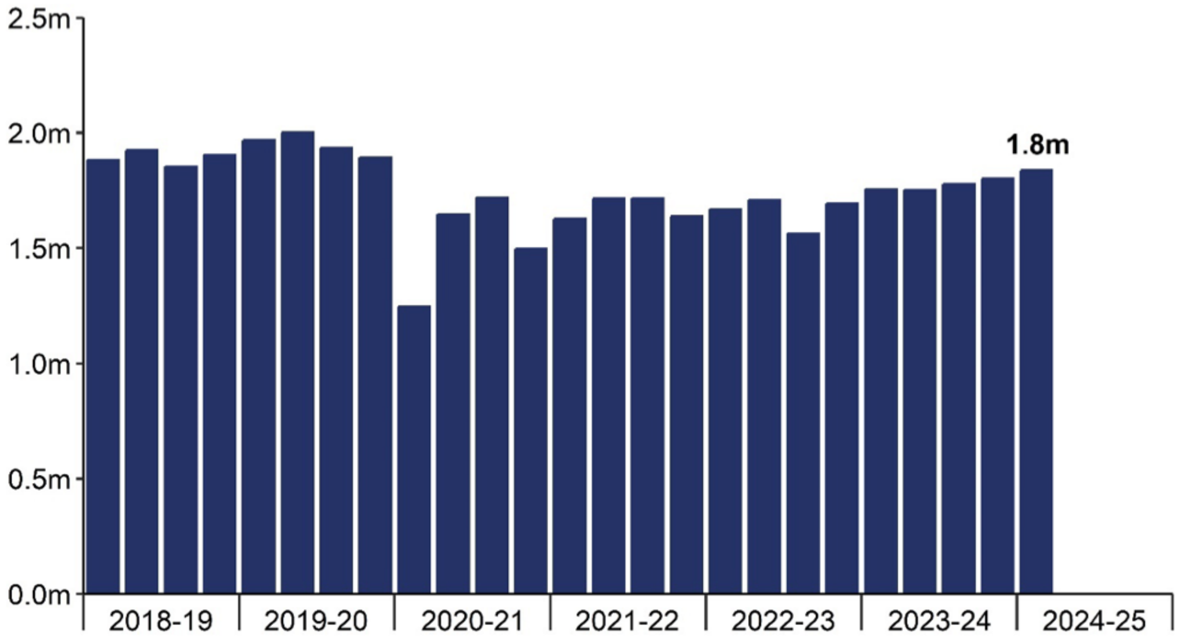



***Figure 2.1 – COVID-19 caused a decrease in the number of scheduled trains in the UK (ORR, 2024):***

Similarly, South Korea's railway operator *KORAIL* reports that, despite passenger numbers returning to normal in 2023, the number of train services run remains at only about 83.9% of pre-pandemic levels (KORAIL, 2023). Passenger numbers in China also saw a significant decline, falling approximately 33.9% from 2019 to 2020 (CEIC, 2024).

Following the initial investigation of our research problem, we identified three key topic areas on which to focus our review. These are: "technical and infrastructural issues", "natural issues" and "human-related issues", which are defined in the introduction to this paper.

To conduct our systematic literature search, we used several different literature and publisher databases, including *Google Scholar*, *Emerald* and *Springer*. Naturally, we were interested in papers whose topics included "artificial intelligence" or "machine learning", as well as the terms "predict", "delay" and "trains" or "railways". In addition, we applied keywords for each specific topic named above. For example, the "human-related issues" topic required additional search terms "congestion" or

"Human", "Error". In total, we selected five papers for review, a shortlist of the "most relevant" papers from each search. Full details of our literature search process can be found in Tables 2.1a, b and c.

| ***Table 2.1a – Breakdown of inclusion/exclusion criteria (Infrastructural)*** | | |
|---|---|---|
| Initial Library | Filter | Num. of papers |
| Google Scholar | "Predictive maintenance for railway signal and track point failures using data and AI" | 18,800 |
| | Date of publication from 2020 to 2024 | 17,200 |
| | Were published in a peer-reviewed journal | 2,910 |
| | Targeted keywords: Filter: signal, track, rail, ai, data | 1,350 |
| | Filter: Journals known for high relevance in engineering, transportation, and science. | 3 |

| ***Table 2.1b – Breakdown of inclusion/exclusion criteria (Environmental)*** | | |
|---|---|---|
| Initial Library | Filter | Num. of papers |
| Google Scholar, emerald and springer | "Railway disruption due to weather conditions", "Impact of seasonal weather on train operations", "Climate change and railway infrastructure", "Extreme weather railway safety and delays", "Temperature effects on railway tracks", "AI-based weather prediction for railways", "Machine learning models for railway delay prediction", "K-means clustering railway delays"," AI applications in railway management", "Real-time weather data for railway management", "Predictive models for railway weather conditions", "Machine learning for short-term weather forecasting", "Railway infrastructure resilience to natural factors"," Operational challenges due to natural factors in railways". | 10,000 |
| | Date of publication from 2020 to 2024 | 4,350 |
| | Citation Count: Used papers that have been cited more than 10 times | 2,234 |
| | Peer-reviewed journal articles and conference papers. | 502 |
| | Targeted keywords: railway, natural factors, AI | 200 |
| | Publication Source: Journals known for high relevance in engineering, transportation, and science. | 4 |

| ***Table 2.1c - Breakdown of inclusion/exclusion criteria (Human Error)*** | | |
|---|---|---|
| Initial Library | Filter | Num. of papers |
| Google Scholar | (("Artificial Intelligence" OR "Machine Learning") AND predict AND delay AND ("passenger trains" OR "railway")) | 22,900 |
| | Were published in a peer-reviewed journal | 82 |
| | Date of publication from 2020 to 2024 | 82 |
| | Published in the English language | 82 |
| | Most Relevant Chosen | 7 |

# 3. Key Findings

## 3.1 Technical and Infrastructural Issues

### *Convolutional Neural Networks (CNNs) in Railway Predictive Maintenance*

Many studies seem to gravitate towards the efficacy of Convolutional Neural Networks (CNNs) for railway maintenance. Mario, Mezhuyev, and Tschandl (2023) looked into how CNNs can spot defects and check the condition of important railway parts. They explain how CNNs can make things safer, reduce inspection times, and cut costs.

### *Applications of CNNs in Railway Maintenance*

(Mario, Mezhuyev, and Tschandl, 2023) point out several key uses of CNNs in railway maintenance. One important use is inspecting railway plugs and pantograph collector strips. CNNs were used to find defects in these components, with about 70% accuracy in controlled tests. This shows that CNNs can help spot problems early and prevent bigger failures in power transmission parts. Another key application is diagnosing issues with wheels and bogies. CNNs have been effective at detecting problems like flat spots on wheels and defects in bogies, with up to 100% accuracy in fault classification during tests. This proves that CNNs could make rail operations safer and more reliable. Visual Inspection Systems (VIS) are also used, which combine CNNs with cameras mounted on trains or tracks to automatically detect surface issues like cracks and wear. This reduces the need for manual inspections while providing high precision.

### *Integration with Sensor Technology*

(Mario, Mezhuyev, and Tschandl, 2023) also talk about how CNNs are combined with sensor tech to boost their capabilities. For example, thermal imaging is used to spot temperature changes that can indicate hidden problems. LiDAR helps create 3D models that allow for more detailed inspections, and GPS ensures that the images stay aligned over time, making monitoring more consistent.

## 3.2 Natural Factors

### *Application of CLF-NET and CNU RTPM Models for Train delay Prediction and Temperature prediction*

Our literature review focused on the effects of natural factors and how it can be predicted. We came across notable research that demonstrates the ability to overcome limitations of traditional approaches with the use of advanced technologies. CLF-NET and CNU RTPM models are notable examples that demonstrate these advancements in models.

CLF-NET, a deep learning model designed and introduced by Huang et al. (2020) handles complex data. It uses 3D Convolutional Neural Networks (3D CNN) to analyse spatiotemporal features like location and object states, helping the model understand patterns over time and space.
The model also incorporates LSTM (Long Short-Term Memory) to handle time-dependent data, such as weather, ensuring it captures the sequence of events. Additionally, it uses a Fully Connected Neural Network (FCNN) to process static data, such as equipment details, allowing it to account for factors that don't change over time. This model can process these various types of data simultaneously which Huang et al. (2020) states; sets the model apart as it outperforms other conventional and state-of-the-art DL models with regards to root mean squared and mean absolute error. This has been proven by testing the model on real railway data, from China and The Netherlands' train lines, and has been noted for showing exceptional performance in predicting train delays.

The Chungnam National University Rail Temperature Prediction model (CNU RTPM), proposed by (Hong, Park and Cho, 2021), predicts rail temperature using XGBoost to thoroughly analyse weather data as well as solar effect data. Multiple weather factors such as air temperature, rainfall, wind speed, as well as cloud cover, are combined with many solar parameters including altitude, azimuth, in addition to Total Solar Irradiance (TSI). The speciality of this model is its ability to predict temperature with unprecedented accuracy, especially temperatures that exceed 40°C, while being integrated with Train Speed Limit Alarm Map (TSLAM) which is a visual warning system, aiding railway operators to quickly identify high risks.

With the evolution of these models, we don't have to rely on simple statistical or regression analysis for prediction which would often use limited data, like air temperature, resulting in low accuracy. Introduction of deep learning through CFL-Net brings a paradigm shift by addressing spatiotemporal dependencies and diverse datasets, while CNU RTPM demonstrates how machine learning can enhance prediction accuracy and operational safety by incorporating complex environmental factors and visualisation.

## 3.3 Human Error

### *BBI-GPR Highlights the Inefficiency of Human Decision-Making*

A study introduced by Singh, Dhanaraj and Kadry (2024) presents a new machine learning model named Barzilai-Borwein Incremental Grey Polynomial Regression (BBI-GPR), intended to predict train delays with greater accuracy and efficiency. This technique improves the prediction accuracy, lowers error rates and reduces the “computational overhead” to overcome the shortcomings of the current prediction models. There are three main components of BBI-GPR: Feature Rescaling, which uses the Barzilai–Borwein Feature Rescaling for preprocessing data, normalising diverse feature scales to ensure computational efficiency; Feature Selection, which involves Incremental Maximum Relevance Minimum Redundant (IMRMR) algorithm selects optimal features by balancing relevance and redundancy, reducing data dimensionality without losing critical information; Prediction: where Grey Polynomial Regression technique predicts delays by analysing temporal patterns and incorporating time-response functions for precise delay estimation.

The model was validated on the ETA train delay dataset, which contains features such as trip IDs, train numbers, station names, inter-station distances, stop times, and actual versus scheduled arrival/departure times. By processing these features, the BBI-GPR model accurately forecasts delays, outperforming popular machine learning methods like XGBoost and XGBoost with Bayesian Optimization (XGBoost-BO). Specifically, BBI-GPR reduces prediction time by 25%, error rates by 27%, and increases accuracy by 7%.

While focusing on computational methods, the paper indirectly highlights human errors which contribute to train delays. These factors consist of operational challenges, such as equipment malfunctions and disruptions, which may be caused by human oversight in maintenance or operations planning, and dispatching inefficiencies, where the necessity for dispatchers to manage delays suggests potential human errors in real-time decision-making and schedule adjustments. Furthermore, because railway plans are complicated and frequently handled by human planners, scheduling disputes can result in inefficiencies and a chain reaction of delays when they do occur. Although not directly caused by human activity, environmental and passenger flow factors can affect the spread of delays since they frequently require human decision-making to manage unfavourable conditions and high passenger numbers.

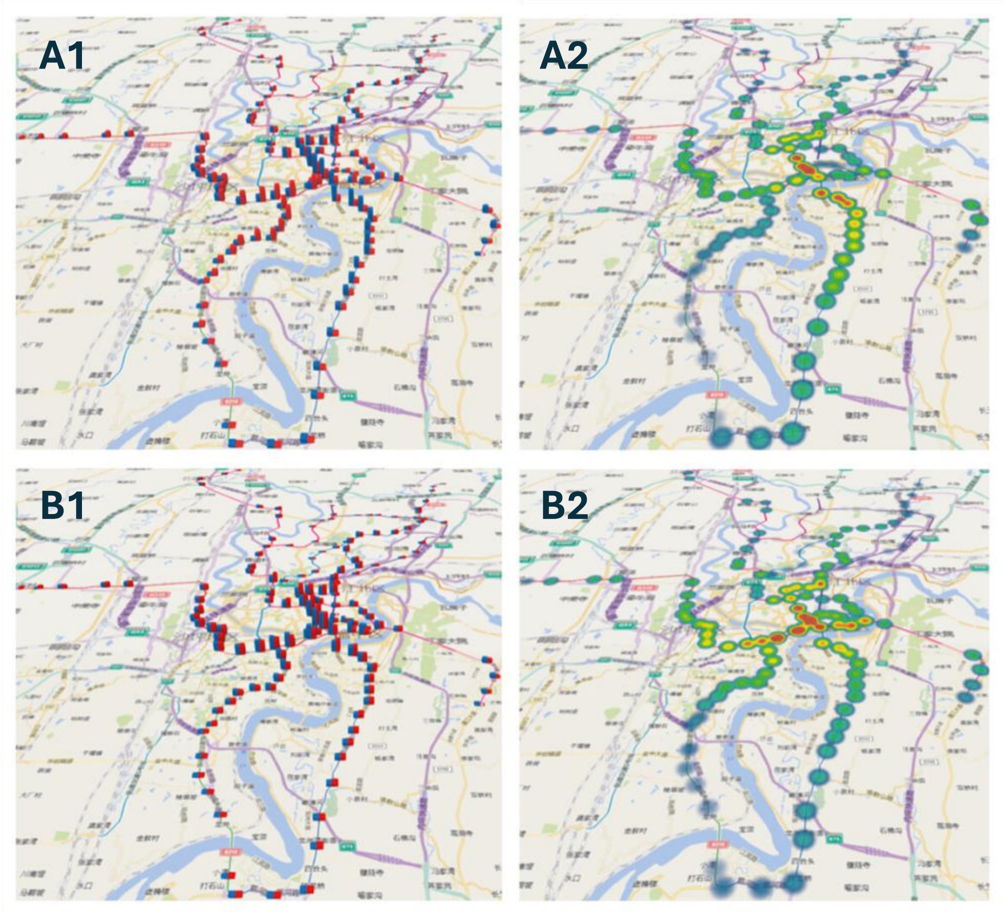
### *Conv-LSTM Predicts Train Dispatch Procedure (TDP) Delays*

Our study also investigated some of the ways that delays due to train dispatch procedures (TDPs) can be mitigated using predictive machine learning. Chen et al. (2021) employed a Conv-LSTM network to predict subway congestion in the short-term. Traditional LSTM is a recurrent neural network (RNN)-based model used for long-term sequence prediction by “retaining” or “forgetting” input data where required. This allows LSTMs to overcome the vanishing gradient problem, where the model struggles to recall information from many steps ago (Greff et al., 2017; Noh, 2021). Conv-LSTM augments LSTM by determining temporal variables with reference to data from other locations (stations) in the network at the same time point. Conv-LSTM then categorises the outputs using supervised convolutional neural networks (CNNs).

In the above study, the Conv-LSTM model took travel card numbers, departure and arrival times, and location data for each passenger from the network. This data was retrieved from automatic fare collection (AFC) data from the Chongqing Rail Transit system in China over 40 working days in 2018.

The performance of Conv-LSTM was compared to five other categorisation algorithms – autoregressive integrated moving average (ARIMA), ANN, CNN, LSTM and fully connected (FC)-LSTM. Three common statistical metrics were used for this comparison – root mean square error (RMSE), mean absolute error (MAE) and determination coefficient ($R^2$). Conv-LSTM performed the best in all tests, with values of 0.0331, 0.0165, and 0.806, respectively. CNNs were the next best overall and FC-LSTM, the improved version of conventional LSTM, was the third best.

Conv-LSTM was then applied to the Chongqing Rail Transit system using four categories of spatiotemporal data – both inbound and outbound passenger flow data from each station; the total number of delayed passengers; and average delay time for all passengers across the network. Unsurprisingly, the study found that peak congestion hours were between 07:30 and 08:30, then again between 17:30 and 18:30, consistent with daily rush hour times (Figure 3.1). Lines 1 and 3 were found to be the most congested, especially in the city centre. Line 1 has multiple major city centre junctions with other lines and Line 3 is one of Chongqing's most popular lines, whilst being the world's longest straddle-type monorail line with relatively few operational trains. Hence, these predictions make intuitive sense and demonstrate the model's reliability.




***<u>Figure 3.1 – Train delay predictions using Conv-LSTM match real delay distributions closely (Chen et al., 2021):</u>***
*Rail delay prediction data for time periods A (07:00-08:00) and B (17:00-18:00). (A2 and B2, where red spots have greater predicted delays) match real train delay data closely (A1 and B1where red and blue bars represent passenger delay distribution for trains travelling upward and downward, respectively).*

Overall, the fact that Conv-LSTM combines the benefits of both LSTMs and CNNs gives it significant advantages over both models, as well as other ML methods. Conv-LSTM can make both short- and long-term predictions, crucial for immediate responses to issues arising on the railway network, as well as planning for the future. Similar methods, such as the gated recurrent unit (GRU), also utilise input and output gates. GRU reduces computational time compared to LSTMs because the "input" and "forget" gates are combined into a single "update" gate (Shiri *et al.* 2023). However, this reduces the computational capacity of GRU and makes it more likely to forget input variables over time, leading to the vanishing gradient problem. Hence, GRU falls down in long-term predictive capabilities, crucial information for the railway network, compared to LSTM.

## 4. Discussion

In this literature review, we have presented a selection of machine learning models applied to mitigating railway delays from across the world in recent research. Using studies which exclusively predicted delays, as outlined in the introduction to this paper, we identified recurring threats to train timetabling and categorised them into 3 key topics. These were "technical and infrastructural issues", "natural issues" and "human-related issues". We then used these categories to systematically search for and identify the most relevant research papers for our review.

It has been somewhat surprising to discover just how many different ML methods have been used in train schedule management studies. However, the range of methods reflects the diversity and scale of issues faced by the railway network and highlights how difficult it is for railway operators to maintain network itineraries. The reason that so many different ML methods are used is due to each method's specific advantages compared to others. For example, CNNs can take many different types of input data at once but require high computational power to do so. Combining CNN with LSTM in Conv-LSTM reduces the volume of input data for the CNN to handle, streamlining the categorisation process. Correspondingly, the variation in the data types considered makes designing models very challenging. All kinds of input data need to be considered, from passenger flow data and infrastructural defects to even more unpredictable variables such as weather and lighting conditions. These factors can introduce high degrees of uncertainty into any calculations made and can compromise both input data quality and model accuracy.

Overall, the ML models that we have presented offer a notable option for train delay prediction. In most cases, the proposed model predicts delay occurrences, scale and duration with a good level of accuracy and reliability, even when compared to other similar ML models. However, despite the considerable progress that these papers represent, many studies fail to apply their model to an entire railway network. This is often because of the computational demand that the model requires. The model could take many minutes to simulate the network and make predictions. By which time, trains would already be late by ORR's 1-minute-late definition. This is not even considering the time required for railway operators to interpret the model's output and communicate the results to relevant services. Therefore, in the real-world, railway operators would still face significant delays to response time and, ultimately, train scheduling.

Even though each of our studies showed different levels of success, it's important to remember that the UK works very differently in terms of sociology to other countries. For example, a lot of the countries we investigated have fairly homogenous populations, which brings its own implications. By focusing our investigation on countries with similarly high population density to the UK, we attempted to "normalise" this variable in terms of the strain on the country's railway network. On the other hand, the UK's diversity creates unique challenges and opportunities, especially when it comes to creating solutions that are fair and inclusive. This makes it clear that we need to think about local sociological contexts before applying ideas from other places.

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# Accompanying Report

**Submission Date: 12th December 2024**

| *Table 1 - Group Members and their Sub-Topics* | |
|---|---|
| **Group Members** | **Sub-Topics** |
| Benjamin Yiu | Technical and Infrastructure Issues |
| Fia Proffitt | Technical and Infrastructure Issues; Introduction |
| Michael Nwabuoku | Technical and Infrastructure Issues; Systematic search tables |
| Jiwon Lee | Natural Factors |
| Prathusha Wijesinghe | Natural Factors; Accompanying report |
| Jintaek Uh | Natural Factors |
| Devarshi Choudhury | Human Error |
| Lucas Pavlou | Human Error; Literature review methods; Discussion |

We were very lucky to start working as a group so early in the semester. It gave us time to plan and figure out how we were going to approach the project. Having that head start meant we could split up tasks, set deadlines that worked for everyone, and handle problems as they came up. It also helped us build a strong sense of teamwork, which made a huge difference in getting everything done.

The weekly meetings were key to keeping us on track. They helped us to stay focused, gave us a chance to share updates, brainstorm ideas, and change things up when we needed to. We played to everyone's strengths, so the work got split in a way that worked for each of us. A lot of us naturally stepped up to take charge at times, making sure we had clear goals and stuck to our deadlines.

We split the project into specific areas to make sure we covered everything. Benjamin, Fia, and Michael handled the technical and infrastructure issues, while Jiwon, Jintaek, and Prathusha focused on natural disruptions, like weather. Lucas and Devarshi took on human errors, like operational mistakes and miscommunication. This way, everyone became experts in their section, and it helped make the final product more well-rounded.

Of course, there were some challenges along the way. Early on, some topics overlapped, like signal failures, which could be seen as both infrastructural issues and human errors. This caused some confusion and some wasted effort but was resolved by talking it through in our meetings and making the boundaries clearer. Time management was also tricky because balancing this project with other classes wasn't easy but starting early and sticking to our weekly meetings helped us stay on top of it.

We also had some issues with resources, like not having access to certain research papers. Luckily, we all worked together to share what we had so everyone could get what they needed. We made sure to stay professional and ethical, crediting our sources properly and keeping things respectful, even when we didn't always agree.

We ultimately decided not to include an abstract in our report due to the 10-page restriction. This was unfortunate, as we felt it would have enhanced our report further and given it some context from the beginning. However, we as a team felt that this was a worthy sacrifice for the remainder of the project.

This project wasn't just about fixing rail disruptions—it also taught us a lot about teamwork. It really showed how important it is to approach problems from different angles and work together to come up with the best solutions. The diversity in our group made the whole experience even better. Our discussions brought up ideas none of us would have thought of on our own. Even with the challenges, this project turned out to be really rewarding for all of us. We're proud of what we accomplished and grateful for the chance to work together.