Predictive Technologies for Strategic House Fire Management

Andrew Edwards  
*Macquarie University*, andrew.edwards2@hdr.mq.edu.au

Stephen Smith  
*Macquarie University*, stephen.smith@mq.edu.au

Peter Busch  
*Macquarie University*, peter.busch@mq.edu.au

Donald Winchester  
*Australian Institute of Business*, Donald.Winchester@aib.edu.au

Follow this and additional works at: [https://aisel.aisnet.org/acis2022](https://aisel.aisnet.org/acis2022)

**Recommended Citation**  
[https://aisel.aisnet.org/acis2022/10](https://aisel.aisnet.org/acis2022/10)

This material is brought to you by the Australasian (ACIS) at AIS Electronic Library (AISeL). It has been accepted for inclusion in ACIS 2022 Proceedings by an authorized administrator of AIS Electronic Library (AISeL). For more information, please contact elibrary@aisnet.org.
Predictive Technologies for Strategic House Fire Management

Full research paper

**Andrew Edwards**
Department of Computing
Macquarie University
NSW, Australia
Email: andrew.edwards2@hdr.mq.edu.au

**Dr Stephen Smith**
Department of Computing
Macquarie University
NSW, Australia
Email: stephen.smith@mq.edu.au

**Dr Peter Busch**
Department of Computing
Macquarie University
NSW, Australia
Email: peter.busch@mq.edu.au

**Dr Donald Winchester**
Australian Institute of Business
Adelaide, South Australia
Email: donald.winchester@aib.edu.au

**Abstract**
House fires have posed a threat to life and property in every society for millennia such that laws, organisations and work systems have been established to protect communities. Motivated by statistics published annually by the Australian Productivity Commission (2021) showing little change in the fatalities, injuries or costs associated with house fires, this research demonstrates that large repositories of publicly available information about house fire incidents can be used to create predictive decision tools that could lower the impact of house fires on society. Interpreted through an activity theory lens, this research demonstrates how data mining can identify common features in public datasets and be used to create predictive models to identify future instances of house fires. The research proposes that this information be used by government, firefighting organisations, insurers, not for profits and the public to better prepare when and where house fires are more likely to occur.

**Keywords** Prediction, Risk Management, Activity Theory (CHAT), House Fires, Machine Learning.
1 Introduction

House/building/structure firefighting is an activity with a long history dating back to the Romans (Kenlon 1913). House fires typically possess a rapid ignition trajectory and are particularly destructive to people, man-made structures, and the environment. Generally, their occurrence increases with correspondent growth in human populations, rapid urbanisation, climate change (FEMA 1997), and they require immediate and coordinated response where timing is critical. A fast response can significantly reduce the consequences of a house fire in terms of loss of life, property, the economy, and environment (Challands 2010). The typical approach to managing house fires is to wait until they start, alert emergency services, who then promptly respond at the location of the house fire; a classic case of this ‘response’ paradigm is noted by Allen et al. (2014). In addition to firefighting, emergency service agencies develop and deliver educational programs on issues of planning and preparation, based on the conviction that with sufficient advanced warning, community education and engagement could prevent fire emergencies from occurring in the first place. House fires destroy lives and livelihoods wherever they occur, but wreak greatest harm where there is least preparation, education, and knowledge sharing (Allen et al. 2014). It is in dealing with such disasters, where information technologies can be useful and IS researchers have made a significant contribution to knowledge in the Emergency Management literature (see Chen et al. 2009), for IS has played a significant role in providing information to strategically manage the traditional activities of firefighters and emergency managers.

This paper recognises efforts in disaster prevention and preparation, including its limitations - thus it investigates the feasibility and efficacy of information systems analysing house fire data collected over many years. Using predictive systems, authorities could forecast the likelihood of probable future instances of house fires, the time and location, so communities and householders are better prepared with firefighting assets better utilised, to save valuable time in responding to a house fire incident, in turn resulting in a greater chance of saving lives, reducing the impacts and damage to property, the economy and environment; these points comprising the research gap addressed here. The challenges of analysing historical data and developing models to forecast pending events in reasonable time, are well known in IS; however, they inevitably require the integration of incompatible datasets, coupled with considerable computation (Chen et al. 2009). Nevertheless, these challenges are reduced, as technology improves. We contribute to the academic literature and practice in two areas: (1) IS decision making in the Emergency Management of house fires; and the adoption of (2) data mining, analysis and modelling, involving multiple large datasets to provide decision support in future events.

Due to the focus on IS decision making, Cultural Historical Activity Theory (CHAT) (Vygotsky 1978; Leontiev 1981; Engeström 1987) is used as an instrumental theory (Davison et al. 2012). Similar, to other firefighting studies (Weidinger et al. 2018), activity is adopted as the unit of analysis where activity represents “a person or group of people (subjects) using the affordances of tools (physical or psychological) as they work at something (the object) to achieve some purpose within a community” (Hasan et al. 2016). CHAT provides a meaningful lens through which to make sense of the different subjective interpretations of activities. In CHAT, mediation is a dynamic two-way process where the capability and availability of tools mediate what can be done, and the tools in turn are modified as more is demanded from them (Crawford and Hasan 2006). Prominent tool-mediated activities in this research include predictive activity involving the purposeful interaction of the subject (households) with an object (decision making on fire safety) using machine learning through a computer application (tool). Consequently, the following research questions (RQ) are answered:

RQ1. How can the likelihood of house fire occurrences be predicted days in advance?

RQ2. How can IS expertise contribute to the development of prediction tools for house fires to aid in decision making?

This paper is organised as follows: first, the literature on IS issues in Emergency Management is reviewed, to establish the context for the study, with the research gap identified. Second, the research approach, design, and justification are presented. Third, the data analysis and development of the solution is presented. Finally, the activity of the research is examined, and the conclusions presented.

2 Literature Review

Although CHAT is commonly known simply as Activity Theory in IS research, this paper acknowledges its cultural-historical tradition (Vygotsky 1978). Indeed, in their use of Activity Theory in a post-analysis Emergency Management study, Chen et al. (2013) recommends the addition of environment/context and timeline, as elements to those of the Engeström’s (1987) framework of activity commonly used in IS studies. The first two sections of this literature review set the cultural-historical context for the research...
in preparation for the third section which subsequently presents literature to support the CHAT analysis of findings.

2.1 IS and Disaster Management Research

In the context of this paper, a significant contribution of IS scholars has followed the seminal work of Simon (1960) dealing with the challenge of collecting data and processing it into information, on which important decisions are based. More recently the emphasis is on intelligence, analytics and big data as articulated by Clarke (2016): “the moderate enthusiasm engendered by ‘data warehousing’ and ‘data mining’ of the 1990s, has been replaced by unbridled euphoria over ‘big data’ and ‘data analytics.’” With respect to the use of IS for Emergency Management, the compilation by van de Walle et al. (2014) provides a comprehensive overview. In addition, there is an abundance of reports where IS is used in Emergency Management, but chiefly at the practitioner level, where researchers aid practitioners to study aspects of emergency incidents, such as ‘fire service response times’ (e.g., Challands 2010). A growing body of IS academic literature focusses on the use of IS in the field of firefighting including spatial analysis (Rohde et al. 2010), and the use of neural networks (Yang et al. 2006) which constitute a smaller body of literature involving predictive capability and modelling socio-economic factors (FEMA 1997; Chhetri 2010). In addition, weather forecasters have a long history of applying statistical analysis to prediction (Lorenc 1986) which relate to concepts presented here. The literature shows the potential of IS/IT to contribute significantly to the field of Emergency Management with technology, communications, data processing capability, decision support and its strategic management. However, there is still much to learn, where (1) large datasets derive from disparate organisations using differing standards and data properties (e.g., types and units), as well as from other sources such as weather bureaus and population records; and (2) the focus is on prediction for future action rather than retrospective analysis. This study acknowledges the risks and challenges of big data analytics, appreciating the examination by Clarke (2016) using examples of projects involving “re-purposing data, consolidating data from multiple sources, applying analytical tools to the resulting collections, drawing inferences, and acting on them.” There is little application of Machine Learning to the domain of house fire prediction from a practitioner or IS perspective, Anderson and Ezekoye (2018) propose a new way to determine general fire risk to single family homes by using house plans to model fire progression rates, Tam et al. (2021) demonstrates the ability of Machine Learning and Internet of Things sensors to predict cook top fires in a laboratory setting and more recently Jha and Zhou (2022) demonstrate the application of Machine Learning in the laboratory to predict wildfire propagation.

2.2 CHAT as an Instrumental Theory

Cultural-historical activity theory (CHAT), also known as Activity Theory, has gained the attention of IS researchers who find it suitable for analysing the design, development, and evaluation of ICT-based systems as well as activities of groups or organisations (e.g., Kuutti 1996; Hasan and Gould 2001; Chen et al. 2013). While Engeström’s Activity System is commonly the basis of the above analysis, other more insightful aspects of the theory are frequently overlooked, namely those addressing the complexities and dynamics of socio-technical systems (Kuutti 1996). While generally supporting Engeström’s model, Blackler (1993) observes that the model assumes some level of agreement will exist in a community of practitioners on the object of their shared activity. In complex organisations, such agreement may not be the case, and there are likely to be divergent interest groups favouring a range of goals and priorities. In this research, activity is adopted as the unit of analysis, which is described by Leontiev (1981) as the minimum meaningful context for understanding complex related sets of actions, and unless the whole activity is the unit of analysis, the analysis is incomplete (Kuutti 1996). Well-known elements of Engeström’s activity system are used as a means of decomposing an activity into smaller units, and also as a framework and language for describing and making sense of the whole activity. The dialectic nature of the subject–object relationship is emphasised such that all stakeholders possess their own subjective understanding of the object of an activity and revisit this as the activity evolves; this can be particularly complicated when objects are shared by different activities and therefore different subjects (Engeström 2007). Finally, activity is considered as a two-way concept where the capability and availability of tools mediate what can be done, and tools in turn are modified as more is demanded from them (Crawford and Hasan 2006). In the complex realm of house fire prediction, CHAT makes sense of issues in a way that informs the activities of the research and thus becomes the instrumental theory.

3 Research Methodology

Given this study involves house fire data to develop predictive modelling for the likely time and place of house fire incidents up to seven days in advance, our aim is thus to produce a scientific decision-making
tool to increase firefighting efficacy. RQ 1 asks how this can be done, whilst RQ 2 asks how this predictive technology can aid in decision making.

McGrath (1981) claimed a single approach to research was a limiting factor, therefore a combination of approaches is likely to provide a more grounded result. Using Saunders et al. (2019) ‘Research Onion’ model, the following methodology is adopted (Figure 1):

![Figure 1: The Research Onion (Saunders et al. 2019) adopted for this study](image)

The research philosophy is Positivism as the output of RQ1 will be predictive models created from data collected from multiple creditable sources aligned to instances of house fires. A deductive approach is taken to answer the research questions building on previously published work (Edwards 2017, Edwards et al. 2019, Edwards et al. 2020) and extending this work using new data and methods to create models to identify the likelihoods of house fires occurring into the future. An experimental approach will be adopted to answer RQ1 from which inferences may be drawn to answer RQ 2. From common features identified in the data collected and aligned, experiments will be conducted to create different models with an operating solution to identify future instances of house fires. The strategy used to answer RQ1 and 2 is Activity Theory - represented diagrammatically in Figure 2 and summarised as follows:

- **The motivation** for the activity is to create one or more models that can be used to identify the likelihood of house fires occurring in the future to create safer communities.
- **The subject** of the activity is the research.
- A variety of **tools** will be used to create models including spreadsheets, programming languages, open-source tools and proprietary cloud-based technology services.
- **The object** of the activity is the creation of one or model.
- **The outcome** is to provide a decision-making tool to reduce instances of house fires.

![Figure 2: The Research Strategy – Activity Theory](image)
The experiments to create the models occurred over a 12-month period from April 2021 to May 2022, which included the creation of a computer program called M2inder using models to predict instances of future house fires. Two datasets were created from publicly available data to identify common features associated with instances of house fires to create the models. The M2inder computer program would harvest and align data based on location from the following sources:

- Australian Bureau of Statistics - Socio-Economic Indexes for Area includes multiple tables on socio economic indicators aligned to location, postcode location, population count - https://www.abs.gov.au/websitedbs/censushome.nsf/home/seifa
- Fire & Rescue NSW – unstructured data on house fires that included location published at https://twitter.com/FRNSW

4 Results and Analysis

The Activity Theory analysis presented in this section provides the answer to RQ 1 - How can the likelihood of house fires be predicted days in advance and RQ 2 - How can IS expertise contribute to the development of prediction tools to aid in decision.

Fire prediction was the activity for which the computer program called M2inder would be developed using a design science loop to iteratively develop and review the software in a series of sprints with the intent it is used to predict the time and locations of future instances of house fires. As the data issued by each organisation (Australian Bureau of Meteorology, Australian Bureau of Statistics and Fire & Rescue NSW) had no common (or primary) key to enable joins to be made, a common feature identified in every dataset was <location>, which included either postcode, suburb, town or weather forecast area and formed the basis on which data would be joined, analysed and the solution for the M2inder application developed. Spreadsheets were created to prepare and analyse results which included the development of tables to align instances of house fires, geospatial data (latitude and longitude), socio-economic data (Socio-Economic Indexes for Area in the form of a decile score from 1 being the lowest to 10 being the highest), demographic data (population count), count of the number of historical house fires and the weather (both forecasts and actual observations). Data was then transferred into a relational database, and the M2inder program exploited to enable further data to be collected and collated automatically. Data was then extracted into spreadsheets for analysis that identified common features for increased house fire likelihood including temperature, temperature differential, location, socio-economic decile, precipitation, and precis forecast (word picture). For example, on very cold days there were greater occurrences of house fires in locations with lower socioeconomic indices.

4.1 Development

Figure 3 summarises the practical activity of building M2inder, emphasising that by predicting the time and location of possible fires, it would allow decision makers to use resources more effectively through asset pre-deployment while warning citizens in selected locations, as indicated on its interface (Figure 4). In presentations and discussions with researchers and interested parties, many people do not comprehend the role of M2inder in predicting house fires. Explained simply it is like a weather forecast but for house fires.

4.2 Implementation

The architecture of the M2inder application (Figure 4) demonstrates a working solution hosted at the National Compute Infrastructure encompassing data ingestion, transformation, storage, modelling and prediction processing, with textual, tabular and map outputs (Figure 5).

4.2.1 Outputs – Forecasts, Lists, Models and Maps

A list of forecasts (Figure 5a) ordered by date from most recent are displayed with the last 30 forecasts appearing on the first page.
Links are available to view forecast information in a tabular format (Figure 5b); or the outputs of the two models to enable easy comparison ranking locations from highest to lowest likelihood (Figure 5c); and a mapping interface by forecast day (Figure 5d). The state-wide list of all locations and forward forecast dates are available. The fire likelihood indicator is published as a set of bars coloured red, ranging from 1 to 10, with 10 being the highest. The interface provides the end user with the ability to extrapolate detailed weather information against house fire likelihood by day for the weather forecast. A map view (Figure 5d) enables a user to pan, scroll and zoom forecasts by date, placing the Fire Likelihood Bar indicator at each forecast location.

---

**Figure 3 – Activity Theory View of M2inder within its operational context**

(adapted from - Engeström 1987, p. 78)

---

**Figure 4 – Activity Theory View of M2inder within its operational context**
4.3 The M2inder and Machine Learning Model

The H2O Flow Machine Learning tool set (https://www.h2o.ai/) was selected to undertake the experiments. The original intention of M2inder and this study, was to collect data over Winter 2021, to examine the accuracy of predictions. The exploratory and Auto Machine Learning experiments also revealed a deep learning model provided optimal results (Figure 6). To progress the actual development of a Deep Learning Model, all weather forecast data for Winter 2021 was extracted from the database (i.e., 51,175 records containing 80 forecast elements for each of the 146 locations). A binary variable was added to each forecast where a house fire had occurred, namely a zero (0) against each record for no fire, and a one (1) for each forecast associated with an instance of a house fire. What resulted was a very clean, structured dataset in a comma delimited file that was loaded into the H2O Flow Machine Learning Toolset. The data was split into a Learning and Training Set and a Deep Learning Model created (Figure 5). The next step was to select a few days during Winter 2021 on which Fire and Rescue NSW published the details of more than one (1) fire occurrence. The forecasts that related to the instances of these fires were then run through the Deep Learning model and results compared to those of M2inder’s in-built likelihood estimations. The findings from the Deep Learning model were then normalized and listed in order of likelihood (from 1 to 146 being the lowest) and compared with the M2inder likelihood scale, which was refactored to indicate a likelihood (from 1 to 10, being the lowest).
5 Results - House Fire Prediction

This research project began with <input> data (see Figure 5) sourced from actual fire cases, weather, demographic, and socio-economic data. The data was transformed with forecasts providing 80 variables across 7 days in advance, for 146 locations - ultimately producing the following two (2) models:

- **M2inder** – a model that considers fires, location, demographics, and temperature changes.
- **ML** - a deep learning model that considers all 80 data elements for each location.

Metrics output the from the H2O Flow Machine Learning tool during training and validation of the Deep Learning Model using standard formula (see [https://docs.h2o.ai/h2o/latest-stable/h2o-docs/performance-and-prediction.html](https://docs.h2o.ai/h2o/latest-stable/h2o-docs/performance-and-prediction.html)) are described in Table 1.

<table>
<thead>
<tr>
<th>Metric</th>
<th>$r^2$</th>
<th>MSE</th>
<th>RMSE</th>
<th>MAE</th>
<th>RMSLE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Explanation</td>
<td>The $r^2$ value represents how well predicted and actual values align. A value closer to 1 represents a closer correlation.</td>
<td>Mean Squared Error (MSE) measures deviation by squaring the errors from the regression line. The smaller the number the better the performance.</td>
<td>Root Mean Squared Error (RMSE) evaluates how well the model is continuous predicting. The smaller the value the better the performance.</td>
<td>Mean Absolute Error (MAE) is the average of the absolute errors in the model with a smaller number indicating better performance.</td>
<td>Root Mean Squared Logarithmic Error (RMSLE) measures the ratio between the actual and predicted values and the corresponding logarithmic value.</td>
</tr>
<tr>
<td>Value</td>
<td>0.774202</td>
<td>0.007604</td>
<td>0.087201</td>
<td>0.019570</td>
<td>0.058677</td>
</tr>
</tbody>
</table>

*Table 1 – Machine Learning - Deep Learning Model validation metrics*

The high-level <output> from these models is shown and summarised in Tables 2 and 3 (Appendix A). Table 2 begins with the “Input Data” and highlights that the same dataset is processed via two models (M2inder and ML), with outputs produced for each model (Note – Outputs, M2inder columns 5 and 8, ML columns 6 and 9), plus predictions for both 7 days and 1 day from the fire. Note the columns under the heading <output> only show days 7 and 1 respectively. Interpretation of the <output> of models (see Table 2 and 3) is based on a ranked listing of values. For both the M2inder and ML model, the results are grouped and ranked. There are 13 groups containing 12 locations each (i.e., 1-13) covering the 146 locations. The lower the ranking, the more likely a fire will occur. For both models a grading of 5 or less indicates a high likelihood, and rankings above this (6-13) represent lower likelihoods. The validation of the outputs is illustrated in “gray” and validates the predicted location of a fire 7 days and 1 day in advance and supports all cases displayed. Table 3 displays days where no fires were predicted or occurred for any selected location (from the 146 forecast locations); correlating justifiably for the non-occurrence of fire cases. The two models produce very similar results from the same initial dataset. The findings of the two models highlight the similarity and validity of resulting outcomes. The results encompass a real-world practical impact. Discussions with fire personnel revealed intrinsic knowledge gathered over a lifetime of firefighting, enabling professionals to recognise days with a higher likelihood of fire, which M2inder and ML mimic (i.e., the output columns in Tables 2 and 3). Therefore, fire fighters, government, not for profits, insurers and households could take preparatory actions if warned. M2inder takes factors associated with socioeconomics, risk of a house fire and weather as inputs, to create an application that at any time, could predict the likelihood of a house fire occurring in the 146 forecast locations (sites) across New South Wales, Australia. Based on the samples analysed in Tables 2 and 3, it is estimated the model provided a high-level accuracy rate in the vicinity of 45-55% prediction of positives with a reduction of 50% to 40% of false positives from 7 days down to 1 day from the occurrence of the fire event. It is important to note that the current fire prediction rate is Zero i.e., this activity is not practiced in industry. With further refinement of the model, higher quality data improvements can be made, producing better predictions in turn contributing to safer communities.

6 Discussion

In answering RQ1: can the likelihood of house fires be predicted in advance; the research demonstrates this is possible by using data analytics and modelling technologies including machine learning. In answer to RQ2, the research demonstrates that IS expertise has driven analysis and development of the M2inder system, identifying predictive patterns representing a significant advance for firefighting, and the synthesis of activities depicted in Figure 2. This project is not solely about building an IT artefact, although this has long been a significant topic in IS research (Orlikowski and Iacono 2001). This study
encompassing M2inder and ML models and its application, provides users with information to consider activities potentially undertaken to reduce house fire impacts, including:

- Issuing warnings on higher likelihood days targeted by locality, such as bushfire, storm, or flood warnings.
- Providing targeted community engagement on the risk of house fires in certain localities.
- Managing resources in localities where there exist higher likelihoods of a house fire occurring.
- Having personnel on standby in localities with a higher likelihood of house fire occurring; and
- Sharing information across government, the Emergency Management sector and the private and not for profit communities, to enable similar engagement and activities to occur.

The generalisability of this research stems from the significance of an exemplar case for research into IS support for predictive programs for house fires, using data from the State of NSW. The findings from this research have broad practical application to many other state governments in Australia and other comparable countries. The claim there is certain generalisability due to the significance of the case and the abstraction of concepts when applying the Activity Theory model, which when abstracted, makes sense for application to other domains and disaster types. Pioneering and creative information systems are required to meaningfully disentangle vast quantities of data collected over several years to address numerous issues (including cultural, community, political, industrial, financial, and legislative), to forecast the regions, areas, localities, or properties with the highest likelihood of a house fire occurring. The research demonstrates that at a high level, the increased likelihood of house fires occurring in towns across NSW can be predicted (RQ1). These predictions could assist government, fire agencies, other organisations, and the community for a higher-level awareness for house fires, on days where the weather forecast identified by M2inder indicates higher fire likelihood, including taking proactive action on warnings, public communication, engagement and education (RQ2). This paper contributes to IS research on disaster management by applying an activity theory lens to prediction using machine learning as the tool. This paper contributes to IS Research by inferring new concepts to activity theory by considering the Artificial Intelligence generated from the machine learning as the subject thus opening a new way to consider application to future studies.

7 Conclusion

In this paper, all academic literature in the IS domain was reviewed, and research gap identified in the application of data analysis as a tool to forecast the likelihood of house fire emergencies. The research demonstrated there are patterns in house fire occurrence and related data that have been used to create predictive models to forecast the likelihood of house fire emergencies days in advance, by high level locality. This research widens the scope of Emergency Management to include prediction as a potential remit for IS scholars; we suggest this perspective is essential for a realistic approach to Emergency Management and prevention. Observations from this research demonstrate that local weather conditions comprise one of the key factors in determining the risk of a house fire occurring. We extended this observation to include other datasets which can be included to formulate dynamic risk models; these include demographics, socio economic status, census data, geospatial information, past response history and lessons learnt, which will form the basis of the data analysis of the M2inder system.

The outcome of this paper is relevant to the IS community, practitioners, emergency service agencies, the insurance industry, not for profits, and governments, to reduce loss of life and property resulting from house fires. Lessons learnt will have implications and generalisable beyond NSW and the firefighting community. Such lessons re-orientate existing data towards a new direction of research in encompassing Machine Learning and Artificial Intelligence technologies and there interaction with people. Significantly these lessons demonstrate that IS expertise can contribute to an understanding of the problem in understanding real house fire predictions. This research conceptualises the complexity of information systems required to create a solution and then delivering it. A challenge to governments and emergency service agencies is translating the increasing trends of emergencies and finding practical solutions using science, while managing gaps in complex data (Aitsi-Selmi et al. 2015). The data collected here is accessible globally. We envisage this research is generalisable to other states, jurisdictions, and countries. Further research in this domain should focus on more detailed data collection including weather, spatial and demographics, available at cost. Extending M2inder using more granular data would produce finer detailed and targeted results in predicting house fire occurrences.
8 References


Kenlon J (1913) Fires and fire-fighters: a history of modern fire-fighting with a review of its development from earliest times. George H. Doran Company.


9 Appendix A

Table 2 – Selected output from both models for days of an actual fire occurrence

<table>
<thead>
<tr>
<th>Date</th>
<th>7 Days from the Fire</th>
<th>1 Day from the Fire</th>
<th>Actual Occurrence of House Fire</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Date</td>
<td>Date</td>
<td>M3inder Likelihood</td>
</tr>
<tr>
<td>14/08/2021</td>
<td>10</td>
<td>30/08/2021</td>
<td>10</td>
</tr>
<tr>
<td>24/08/2021</td>
<td>3</td>
<td>30/08/2021</td>
<td>3</td>
</tr>
<tr>
<td>24/08/2021</td>
<td>9</td>
<td>30/08/2021</td>
<td>9</td>
</tr>
<tr>
<td>24/08/2021</td>
<td>7</td>
<td>30/08/2021</td>
<td>6</td>
</tr>
<tr>
<td>24/08/2021</td>
<td>3</td>
<td>30/08/2021</td>
<td>4</td>
</tr>
<tr>
<td>12/08/2021</td>
<td>10</td>
<td>18/08/2021</td>
<td>10</td>
</tr>
<tr>
<td>12/08/2021</td>
<td>3</td>
<td>18/08/2021</td>
<td>3</td>
</tr>
<tr>
<td>12/08/2021</td>
<td>10</td>
<td>18/08/2021</td>
<td>10</td>
</tr>
<tr>
<td>10/07/2021</td>
<td>3</td>
<td>5/08/2021</td>
<td>3</td>
</tr>
<tr>
<td>10/07/2021</td>
<td>1</td>
<td>5/08/2021</td>
<td>1</td>
</tr>
<tr>
<td>10/07/2021</td>
<td>12</td>
<td>5/08/2021</td>
<td>12</td>
</tr>
<tr>
<td>10/07/2021</td>
<td>3</td>
<td>5/08/2021</td>
<td>3</td>
</tr>
<tr>
<td>10/07/2021</td>
<td>3</td>
<td>5/08/2021</td>
<td>3</td>
</tr>
<tr>
<td>10/07/2021</td>
<td>3</td>
<td>5/08/2021</td>
<td>3</td>
</tr>
<tr>
<td>21/07/2021</td>
<td>7</td>
<td>27/07/2021</td>
<td>7</td>
</tr>
<tr>
<td>21/07/2021</td>
<td>3</td>
<td>27/07/2021</td>
<td>3</td>
</tr>
<tr>
<td>21/07/2021</td>
<td>12</td>
<td>27/07/2021</td>
<td>12</td>
</tr>
<tr>
<td>21/07/2021</td>
<td>8</td>
<td>27/07/2021</td>
<td>8</td>
</tr>
<tr>
<td>14/07/2021</td>
<td>7</td>
<td>20/07/2021</td>
<td>7</td>
</tr>
<tr>
<td>14/07/2021</td>
<td>2</td>
<td>20/07/2021</td>
<td>2</td>
</tr>
<tr>
<td>14/07/2021</td>
<td>6</td>
<td>20/07/2021</td>
<td>6</td>
</tr>
</tbody>
</table>

Table 3 – Selected output from both models for days with no occurrence of a Fire

<table>
<thead>
<tr>
<th>Date</th>
<th>7 Days from the Fire</th>
<th>1 Day from the Fire</th>
<th>No Occurrence of House Fire</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Date</td>
<td>Date</td>
<td>M3inder Likelihood</td>
</tr>
<tr>
<td>24/08/2021</td>
<td>13</td>
<td>30/08/2021</td>
<td>13</td>
</tr>
<tr>
<td>24/08/2021</td>
<td>5</td>
<td>30/08/2021</td>
<td>5</td>
</tr>
<tr>
<td>24/08/2021</td>
<td>1</td>
<td>30/08/2021</td>
<td>1</td>
</tr>
<tr>
<td>24/08/2021</td>
<td>2</td>
<td>30/08/2021</td>
<td>2</td>
</tr>
<tr>
<td>24/08/2021</td>
<td>12</td>
<td>30/08/2021</td>
<td>12</td>
</tr>
<tr>
<td>12/08/2021</td>
<td>8</td>
<td>18/08/2021</td>
<td>8</td>
</tr>
<tr>
<td>12/08/2021</td>
<td>2</td>
<td>18/08/2021</td>
<td>2</td>
</tr>
<tr>
<td>30/07/2021</td>
<td>1</td>
<td>5/08/2021</td>
<td>1</td>
</tr>
<tr>
<td>30/07/2021</td>
<td>2</td>
<td>5/08/2021</td>
<td>2</td>
</tr>
<tr>
<td>30/07/2021</td>
<td>12</td>
<td>5/08/2021</td>
<td>12</td>
</tr>
<tr>
<td>30/07/2021</td>
<td>6</td>
<td>5/08/2021</td>
<td>6</td>
</tr>
<tr>
<td>30/07/2021</td>
<td>5</td>
<td>5/08/2021</td>
<td>5</td>
</tr>
<tr>
<td>23/07/2021</td>
<td>4</td>
<td>27/07/2021</td>
<td>4</td>
</tr>
<tr>
<td>23/07/2021</td>
<td>9</td>
<td>27/07/2021</td>
<td>9</td>
</tr>
<tr>
<td>23/07/2021</td>
<td>12</td>
<td>27/07/2021</td>
<td>12</td>
</tr>
<tr>
<td>22/07/2021</td>
<td>6</td>
<td>27/07/2021</td>
<td>6</td>
</tr>
<tr>
<td>14/07/2021</td>
<td>7</td>
<td>20/07/2021</td>
<td>7</td>
</tr>
<tr>
<td>14/07/2021</td>
<td>4</td>
<td>20/07/2021</td>
<td>4</td>
</tr>
<tr>
<td>14/07/2021</td>
<td>9</td>
<td>20/07/2021</td>
<td>9</td>
</tr>
<tr>
<td>14/07/2021</td>
<td>4</td>
<td>23/07/2021</td>
<td>4</td>
</tr>
</tbody>
</table>

Positives 40% 50% 60%