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Association Rule Mining for Accidental Dwelling Fire Incidence Data Analysis in Greater Manchester, UK

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ABSTRACT

Association rule mining was used to identify patterns in accidental dwelling fire incidents attended by Greater Manchester Fire and Rescue Service over the period 2013/14 to 2023/24. The association rule mining process identified relationships between cooking fire incidence, distraction, living alone, deprivation, and fire injury. The association rule mining was undertaken using the Python programming language utilizing the apriori algorithm to find frequent combinations of accidental fire circumstances, and the association rules function to find meaningful associations in terms of which combinations of circumstances are most strongly associated with specific fire outcomes. The parameters of the apriori and association rules functions were adjusted in order to produce the most informative and useful set of association rules from the accidental dwelling fire incident dataset. The strength of the relationships was assessed using three key metrics: support, which quantifies the frequency of a rule's occurrence within the dataset; confidence, which determines the proportion of instances where the rule holds true; and lift, which indicates the extent to which the rule's occurrence exceeds what would be expected by chance. Distraction appeared to substantially increase the risk of cooking fires (60% more likely than chance), and distraction appeared to be a more common fire incidence factor in deprived areas. This extends previous research into accidental dwelling fire incidence in relation to deprivation and cooking fires by providing the probabilities associated with co-occurrence of different fire risk factors.

1 | Introduction

Fire and Rescue Services in the UK increasingly view data science and artificial intelligence as a strategic tool that helps to save lives, reduce risk, and optimize resource allocation ([1–3]). These approaches, including statistical analysis and machine learning, offer capabilities that extend beyond traditional analytical methods, enabling the detection of subtle patterns in fire risk that might otherwise go unnoticed [4]. Currently, their effective implementation still requires human interpretation and expertise [5]. Machine learning (ML) models can assist in identifying high-risk households or neighborhoods,

prioritizing home safety visits, with far greater precision than relying on historical averages alone. Among these techniques, Association Rule Mining (ARM) is a data mining approach capable of discovering meaningful frequency-based patterns within datasets. By analyzing the co-occurrence of items or conditions, it can reveal hidden relationships, highlight underlying trends, and inform decision-making. When applied to fire incident data, ARM can reveal hidden relationships [6] which can help shape prevention campaigns, inspections, and resource allocation. In particular, it can be useful for identifying clusters of risk factors that suggest where prevention work will have the biggest impact in order to develop more

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targeted community safety interventions. In this article, the use of ARM for analysis of accidental dwelling fire incidence in Greater Manchester Fire and Rescue Service over the period 2013/14 to 2023/24 is examined. Accidental dwelling fires were the focus of the research because they can cause the greatest harm to individuals, can occur in the most vulnerable settings, and exhibit patterns that allow fire and rescue services to prevent them more effectively than other types of fire [7]. Fires were restricted to those classed as accidental because deliberate fires arise from different motivations and behavioral patterns, are subject to separate investigative and enforcement processes, and are not as amenable to the same prevention-focused interventions (such as home safety visits and behavior change campaigns) that this research is intended to inform.

Association rule mining analyzes a data set to uncover relationships where a given set of items or conditions (antecedents) suggest or predicts the occurrence of another set of items or conditions (consequents). These relationships are expressed in the form of rules, which are derived from the data and quantified using mathematical notation. Formally, let:

X = antecedent (a set of items or conditions).

Y = consequent (another set of items or conditions).

where X and Y are item sets, typically subsets of a universal set of items (the complete set of possible values that could appear in a data set), then association rules are written in the form:

$$X \rightarrow Y$$

To assess the strength and relevance of these rules, different key measures are used:

Support indicates how frequently both the antecedent and the consequent appear together in the dataset (how often X and Y occur together):

Support ($X \rightarrow Y$) = $P(X \cup Y)$ (Probability of X and Y occurring)

Confidence measures the likelihood that the consequent occurs when the antecedent is present (how often Y occurs when X occurs):

Confidence ($X \rightarrow Y$) = $P(Y | X)$ (Probability of Y given X)

Lift evaluates how much more likely the consequent is to occur given the antecedent, compared to chance (how much more likely Y is given X , compared to chance):

Lift ($X \rightarrow Y$) = $P(Y | X) / P(Y)$ (Probability of Y given X divided by the probability of Y occurring)

These metrics collectively help determine whether a rule is statistically meaningful and practically useful, guiding the interpretation of patterns found in the data. ARM is appropriate for the analysis of fire and rescue service data because fire incident records contain categorical data, have reasonable data volumes (thousands of fire incidents per year), and fires are multi-factor involving many circumstances that may interact in non-linear ways. Fire and rescue services can use ARM to uncover

co-occurring patterns in data that are not obvious from simple frequency counts or regression models [8].

2 | Literature Review

2.1 | Accidental Dwelling Fire Prevention

Previous research of accidental dwelling fires in the UK indicated that cooking fires were typically the most common type of accidental fire [9] based on a study in Merseyside. The risk of cooking fire injuries in Merseyside was higher for the elderly and for those in deprived areas. In the UK, deprivation has been associated with the likelihood of accidental dwelling fires [10, 11]. There have been numerous approaches to accidental dwelling fire prevention as part of community fire risk reduction initiatives adopted in various countries which typically involve prevention strategies based upon analysis of frequency of fire incidents [12–14]. In England, home fire safety assessment [15] is typically the main accidental dwelling fire prevention approach used by fire and rescue services. A home fire safety assessment involves providing fire safety advice and equipment to householders dependent on the level of fire risk. A home fire safety assessment includes the health of householders, the home environment and the daily household activities, in order to understand the level of fire risk and provide the best advice for householders. Eligibility for home fire safety assessments is typically based upon analysis of previous accidental dwelling fire incidence. Typically, in England, home fire safety assessments are mainly targeted to those over 65 [16]. Some English fire and rescue services provide an online home fire safety check tool to determine eligibility. Individuals not eligible for a home fire safety assessment can be provided with personalized fire safety advice at the end of the online check [15].

2.2 | Association Rule Mining

ARM was first defined by Agrawal in 1993 [17]. ARM uncovers hidden co-occurrence patterns in datasets, and is used by organizations needing to understand behavioral, operational, or transactional relationships [18]. ARM is an unsupervised machine learning technique that uncovers if then patterns in datasets, showing which items or attributes tend to appear together [19]. It is classified as unsupervised learning, since it does not predict the value of a target variable but instead uncovers structure and co-occurrence patterns in the data [20]. The main evaluation metrics for association rule mining are Support (which indicates rule importance), Confidence (which indicates rule reliability), and Lift (which indicates association strength), with additional metrics such as Leverage (which indicates how much more (or less) often items occur together than expected under independence), and Conviction (which indicates directional implication strength) available for deeper analysis [21, 22].

ARM has been used in sectors such as retail analytics to discover which products are frequently purchased together [23], financial services to detect patterns in customer transactions, credit behavior, and fraud [24], healthcare to identify relationships between symptoms, diagnoses, treatments, and outcomes

[25–27], policing to detect patterns in crimes [28], risk analysis [29, 30], and accident investigation [31–33].

2.3 | Association Rule Mining for Fire Prevention

ARM has been used for the analysis of wildfire incidents [34–37], petrochemical fire incidences [38] and structural fire incidents [39], but does not appear to have been applied specifically to accidental dwelling fire incidence analysis. Cha et al. [34] in a study in Canada, found that lightning and wildfires occur in two distinct areas: frequent wildfire regions with a high frequency of lightning, and frequent wildfire regions with a low frequency of lightning. Dong et al. [35] in a study in China found relationships between the risk of wildfires and the level of rainfall and temperature. Wei et al. [37] in a study in America identified relationships between wildfires and firefighting resource requirements. Jain et al. [36] compared different types of machine learning that could be used for wildfire analysis. Chen and Ye [38] in a study in China examined the relationships between different petrochemical fire risk factors. Mahmood et al. [39] found in a study in Basra city, in Iraq that electrical fires were the most common structural fire cause, followed by carelessness by children, then smokers' materials and that city center locations were more at risk of structural fires.

ARM is suited to accidental dwelling fire analysis because fire and rescue services routinely collect categorical variables such as fire incident types, contributory factors, property characteristics, and deprivation indices that can be analyzed using ARM [40]. ARM is appropriate for accidental dwelling fire analysis because it can identify co-occurring fire risk factors. ARM is a valuable analytical tool because it can identify non-obvious co-occurrence patterns without requiring a pre-defined target variable, complementing supervised machine learning approaches that are primarily optimized to predict specified outcomes and may therefore underemphasise broader interaction structures. In addition, ARM facilitates the analysis of interactions among categorical variables and produces transparent rule-based outputs that fire and rescue service operational staff can readily interpret and act upon. The originality of the research concerns the examination of how ARM can be used for identifying accidental dwelling fire incidence patterns based upon actual accidental dwelling fire incidents attended by Greater Manchester Fire and Rescue Service over the period 2013/14 to 2023/24.

3 | Research Method

This research utilized the apriori algorithm to find frequent itemsets and association rules functions to identify association rules in the Greater Manchester accidental dwelling fire incidence data containing 22 207 records covering the period 2013/14 to 2023/24. The apriori algorithm begins with a search for frequent single items and counts how often each item appears. Only those items whose counts exceed a minimum support threshold (the proportion of records in the data set containing the item) are retained. The algorithm then builds larger itemsets from these frequent items in a structured, step-by-step manner. First, it combines all pairs of frequent single items and checks whether these pairs meet the minimum support threshold used

earlier. Next, the algorithm combines frequent pairs into triplets, but only if all possible subsets of the triplet have already been confirmed as frequent. This ensures that no unnecessary combinations are evaluated, as any itemset containing an infrequent subset cannot itself be frequent, a principle known as the apriori property. The process repeats for itemsets of increasing size (e.g., quadruplets, quintuplets etc.) until no further frequent itemsets can be generated. Once all frequent itemsets are identified, the ARM approach proceeds to generate association rules by splitting these itemsets into antecedent (X) and consequent (Y) pairs. The strength and relevance of each rule are evaluated using support, confidence, and lift. Rules that meet user-defined thresholds for these metrics are retained as meaningful associations, revealing patterns such as which combinations of risk factors are most strongly associated with specific fire outcomes. The research utilized the mlxtend Python library to implement ARM. The apriori algorithm within the mlxtend library was used to find frequent itemsets from which association rules were generated using the association_rules function. The association rule mining was undertaken in Python as Microsoft Excel and Microsoft Power BI, tools that are often used or are being adopted by UK fire and rescue services do not have built-in support for association rule mining.

The accidental dwelling fire incident data included the Indices of Multiple Deprivation (IMD) decile of the Lower Super Output Area in which the fire incidence occurred, the type of fire (categorized by the source of ignition), the type of household (e.g., Lone person under pensionable age, Couple both under pensionable age with no children, Lone parent with dependant child/ren), factors relating to the fire incident (e.g., distraction, falling asleep/asleep, medical condition/illness), Harm (e.g., injury, fatality), and victim age. The victim age variable was categorized into ordinal age bands ("0–17", "18–34", "35–49", "50–64", "65–74", "75+"). These categorical variables were selected for analysis since they had been identified by previous research as being common accidental dwelling fire factors [10, 11, 41, 42]. The IMD decile is a measure of deprivation used in England consisting of a scale ranging from 1 denoting the 10% most deprived areas (Lower Level Super Output Areas, which are geographical areas in England with a typical average of 1500 residents or 650 households [43]) in England to 10, denoting the 10% least deprived areas [44].

The research questions addressed by the research were:

- How can association rule mining be used for accidental dwelling fire incidence analysis?
- How can association rule mining output be interpreted for accidental dwelling fire incidence analysis?
- How can association rule mining support accidental dwelling fire prevention?

These are important research questions, since accidental dwelling fire risk analysis and fire prevention can reduce deaths, injuries, and long-term harm in the place where people are most vulnerable, their own homes. Fires in domestic settings remain the leading cause of fire-related fatalities, and targeted, data-driven fire prevention can be one of the most effective ways to protect the public. Risk analysis using approaches such as ARM

can provide an evidence base for identifying who is most at risk and where fire prevention efforts may have the greatest impact. Accidental dwelling fire prevention has been determined to be cost-effective [45]. The societal and economic cost of a dwelling fire injury is high, and proactive interventions are far cheaper than emergency response and post-incident recovery.

4 | Association Rule Mining for Accidental Dwelling Fire Prevention

4.1 | Using Association Rule Mining for Accidental Dwelling Fire Incidence Analysis

The parameters of the Apriori and association rules functions within the mlxtend Python library were adjusted in order to produce the most informative and useful set of association rules from the accidental dwelling fire incident dataset. In particular the `min_support` parameter of the `apriori` function was adjusted to control how frequent an itemset must be to be considered frequent. The `min_support` parameter sets the minimum proportion of records in which an itemset must appear for it to be kept; in this manner it filters out itemsets that are too infrequent to be useful. A higher `min_support` value generates fewer itemsets, however, interesting infrequent patterns may be missed. A lower `min_support` value will capture rarer associations. The `min_threshold` parameter of the association rules function was adjusted to set the minimum value of the chosen metric (e.g., confidence, lift) that an association rule must meet to be included in the output. It is essentially a filter applied after the association rules are generated. These parameters enabled quality control within the association rule mining analysis. A high level of confidence implies strong predictive reliability, a high level of lift implies non-random meaningful associations.

In order to identify meaningful rules from the dataset, a sensitivity analysis was undertaken. First, the `min_support` parameter of the `apriori` function was incrementally adjusted from 0.01 to 0.05 to determine how many itemsets were identified at different frequency levels. This step aimed to assess the stability of

the frequent itemsets, identify whether the dataset was sparse (when most items rarely occur together, or when most records contain only a small number of the possible items), and locate any “cliff-edges” where small changes in support caused rules to appear or disappear.

Next, the confidence thresholds were varied by adjusting the `min_threshold` parameter from 0.2 to 0.6 while using confidence as the evaluation metric. This was used to assess how predictive the rules were, and whether confidence remained stable or collapsed at higher thresholds, indicating which rules were robust and which were borderline.

Finally, the lift `min-threshold` parameter of the `association_rules` function was incrementally adjusted from 1.0 to 1.6 to determine whether lift values were being inflated by rare items and to evaluate how sensitive lift was to frequency imbalance. Frequency imbalance refers to situations where some items appear very frequently in the dataset while others appear very rarely, resulting in a distribution where a few items dominate the records and most occur only occasionally.

Varying the `min_support` parameter affects which frequent itemsets are generated, while varying the `min_threshold` values for confidence and lift affects the predictiveness and randomness of the resulting rules. This approach makes it possible to observe how the number, strength and stability of the rules change across the parameter settings. If small changes in `min_support` cause large changes in the rule count, the dataset contains sparse or weakly co-occurring itemsets. If rules disappear as confidence thresholds increase, the rules are not strongly predictive. If lift is highly sensitive, meaning small changes in the lift threshold cause large changes in the number of rules, then the dataset may have imbalanced item frequencies. Rules that persist across many parameter combinations are highly stable and therefore more likely to be meaningful. Figure 1 shows the number of frequent itemsets compared to the `min_support` parameter value and indicates that the dataset has many low-frequency patterns, and increasing support quickly eliminates most rules meaning the variables co-occur infrequently.

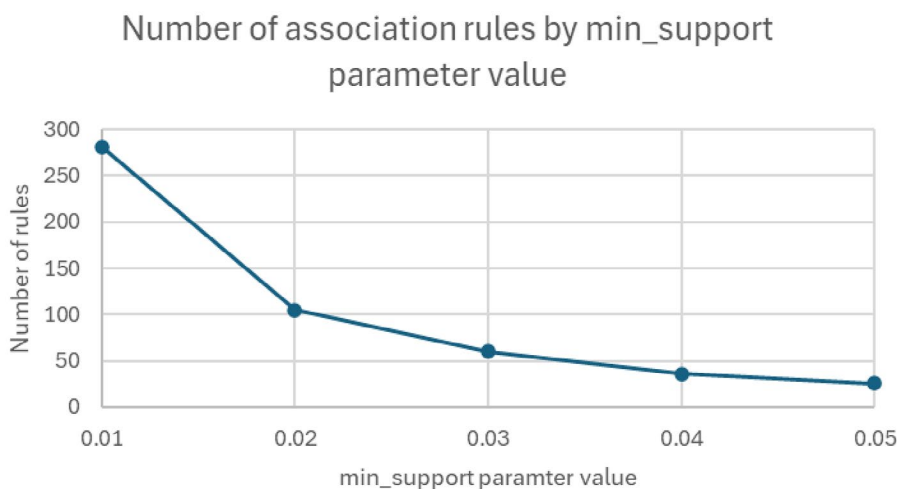


FIGURE 1 | Number of association rules by minimum support threshold, showing that the number of rules identified falls sharply as the support threshold increases, indicating that most itemsets in the dataset occur only infrequently.

Figure 2 shows the number of rules identified compared to the confidence min_threshold parameter value and indicates that many rules have low to moderate confidence (how often the rule is correct when the antecedent occurs), but only a small subset are strong predictors. This helps to identify the most reliable associations.

Figure 3 shows the number of rules identified compared to the lift min_threshold parameter value and indicates that many of the association rules have weak or moderate lift (how much more likely the items occur together than by chance); however, a smaller subset shows strong, meaningful associations.

Overall, the sensitivity analysis showed that support filters out rare patterns, confidence filters out unreliable rules, and lift filters out rules that don't represent true associations. The consistent pattern that higher thresholds imply fewer rules means the association rule mining for this dataset behaves normally.

4.2 | Interpreting Association Rule Mining Output for Accidental Dwelling Fire Incidence Analysis

Table 1 shows the most meaningful association rules in terms of support, confidence, and lift generated from the Greater Manchester accidental dwelling fire incident data from 2013/14 to 2023/24.

Figure 4 graphically shows a comparison of the association rules in terms of support (rule importance), confidence (rule reliability), and lift (shown as labels on data points on the graph, indicating rule strength). The scatterplot of support, confidence, and lift helps to visualize which association rules are frequent, reliable, and meaningful beyond chance. Support shows how often a rule occurs, confidence shows how reliably the consequent follows the antecedent, and lift shows whether the rule reflects a real association rather than coincidence.

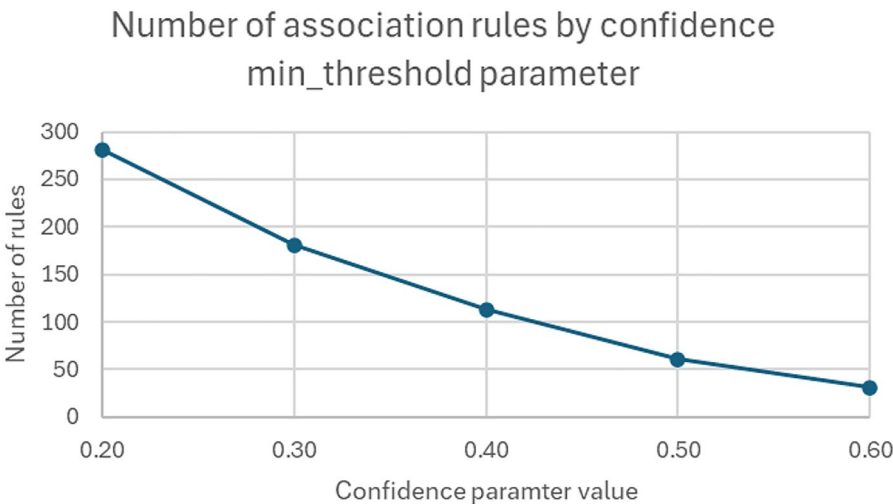


FIGURE 2 | Number of association rules by minimum confidence threshold, showing that the majority of rules have low to moderate confidence, with only a small subset meeting higher confidence thresholds and therefore qualifying as strong predictors.

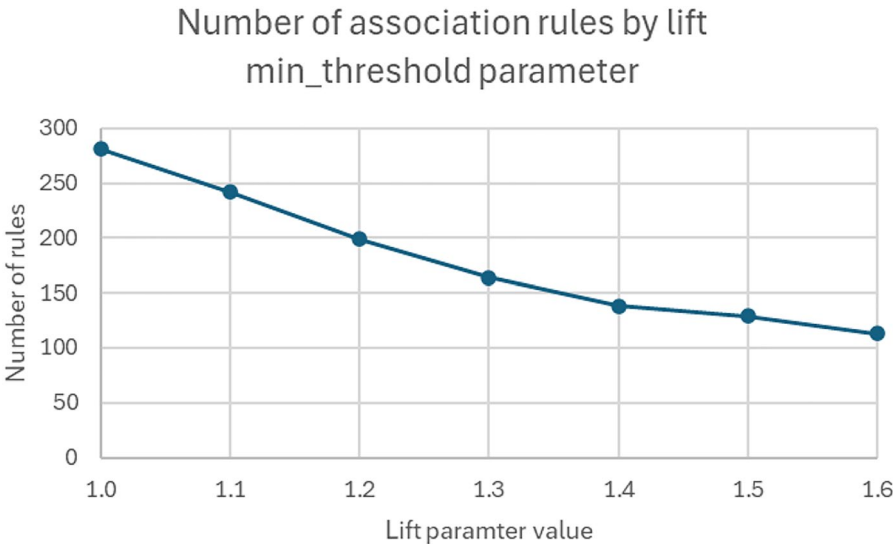


FIGURE 3 | Number of association rules by minimum lift threshold, showing that most rules have weak or moderate lift, with a smaller subset showing lift values well above 1, indicating genuine (non-chance) associations.

TABLE 1 | Association rules from Greater Manchester accidental dwelling fire incident data 2013/14 to 2023/24.

Antecedents	Consequents	Support	Confidence	Lift
Cooking appliance	IMD 1	0.14	0.43	1.14
Lone person < 65	IMD 1	0.09	0.46	1.23
Distraction	IMD 1	0.10	0.40	1.07
Injury	IMD 1	0.08	0.39	1.03
Cooking appliance	Lone person ≥ 65	0.08	0.25	1.27
Cooking appliance	Lone person < 65	0.07	0.23	1.22
Cooking appliance	Distraction	0.13	0.38	1.60
Cooking appliance	Injury	0.07	0.22	1.10
Lone person ≥ 65	Distraction	0.06	0.33	1.37
Injury	Distraction	0.05	0.26	1.10

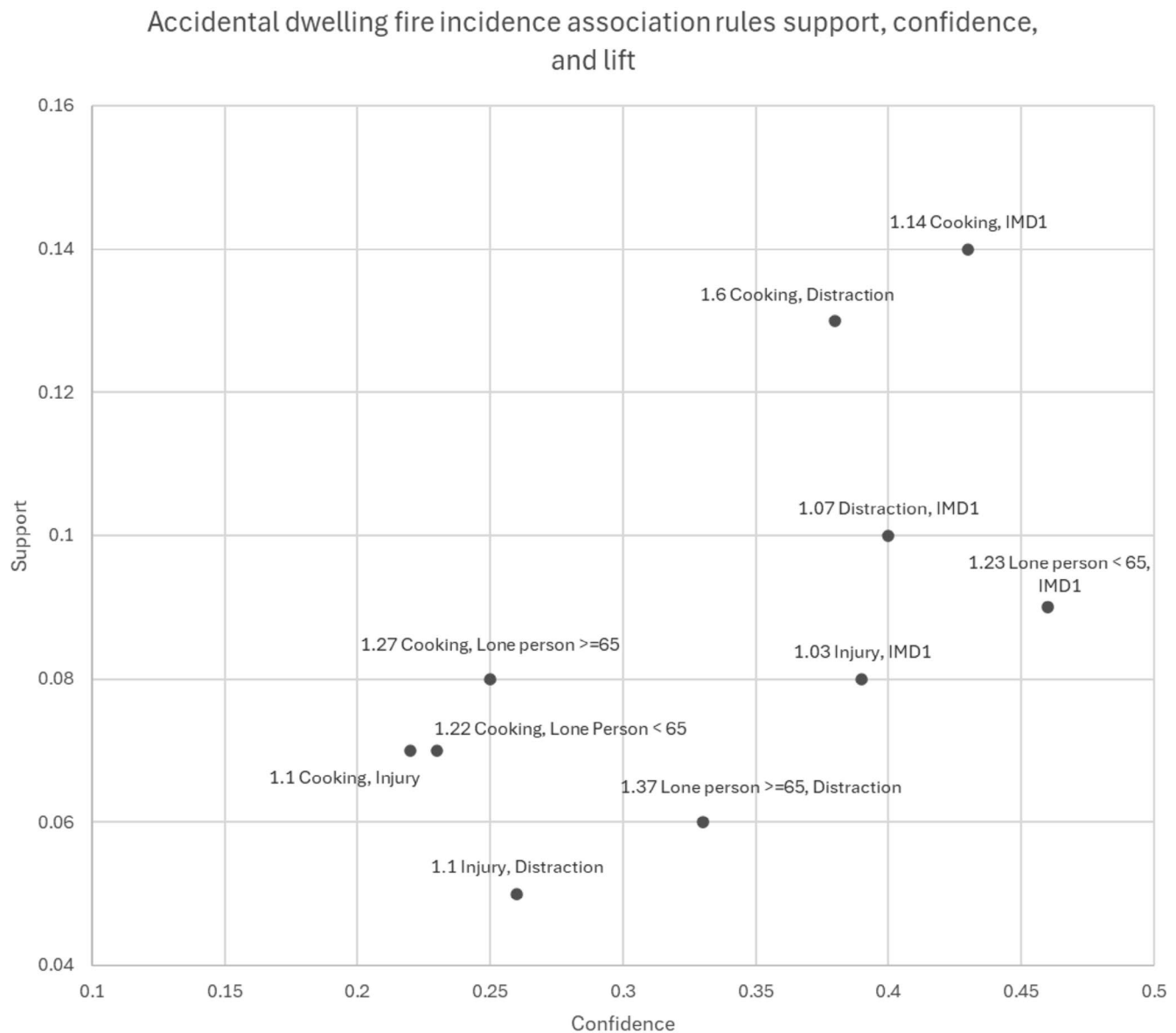
**FIGURE 4** | Scatterplot of accidental dwelling fire incident association rules showing rule importance (support), rule reliability (confidence), and rule strength (lift).

Figure 5 shows the number of accidental dwelling fire incidents where distraction was a factor by type of fire and indicates that cooking fires were by far the most common type of accidental dwelling fire, and that distraction was a factor in 38% of such fires.

Figure 6 shows the number of accidental dwelling fires and cooking fires by IMD decile and indicates that cooking fires account for a higher proportion of accidental dwelling fires in more deprived areas (58.2% of accidental dwelling fires in IMD 1 compared to 41.6% of accidental dwelling fires in IMD 10).

Figure 7 shows the number of accidental dwelling fires and lone person fires by IMD decile and indicates that lone person fires account for a higher proportion of accidental dwelling fires in more deprived areas (53.1% of accidental dwelling fires in IMD 1 compared to 32.7% of accidental dwelling fires in IMD 10).

Figure 8 shows the number of accidental dwelling fires and fire injuries by IMD decile and indicates that the proportion of accidental dwelling fires resulting in fire injury is higher in more

deprived areas (21.0% of accidental dwelling fires resulting in fire injury in IMD 1 compared to 16.0% of accidental dwelling fires resulting in fire injury in IMD 10).

Figure 9 shows the number of accidental dwelling fires and those involving distraction by IMD decile and indicates that the proportion of accidental dwelling fires involving distraction is higher in more deprived areas (25.6% of accidental dwelling fires involving distraction in IMD 1 compared to 19.7% of accidental dwelling fires involving distraction in IMD 10).

In terms of interpreting the results from the association rule mining, antecedents are the IF part of a rule, that is the conditions that must be present. For example, Cooking appliance indicates that the fire incident concerned a cooking appliance, Lone person < 65 indicates that a non-elderly person living alone was involved in the fire incident. Consequents are the THEN part of a rule, that is the outcome associated with the antecedent, for example IMD1 indicates that the fire incident occurred in an IMD decile 1 Lower Super Output Area. Support concerns the proportion of all accidental dwelling

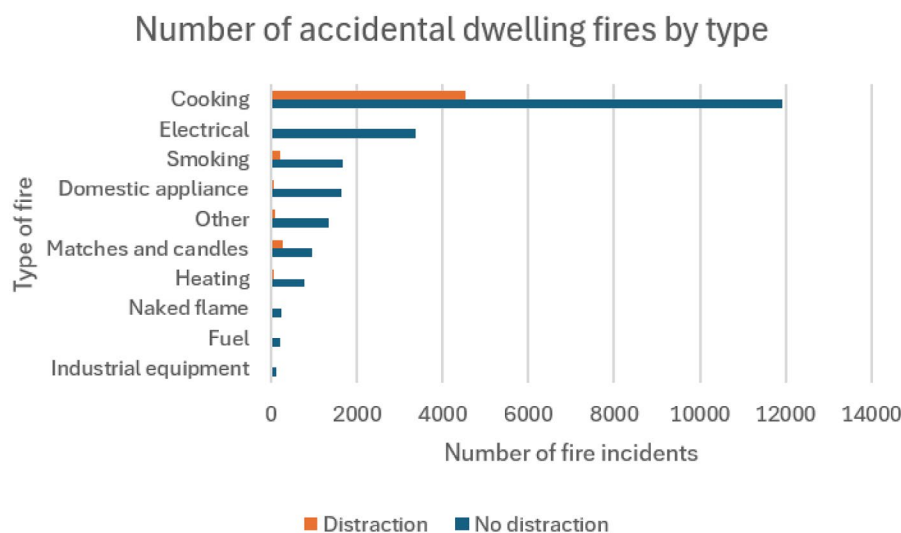


FIGURE 5 | Number of accidental dwelling fire incidents where distraction was a factor by type of fire.

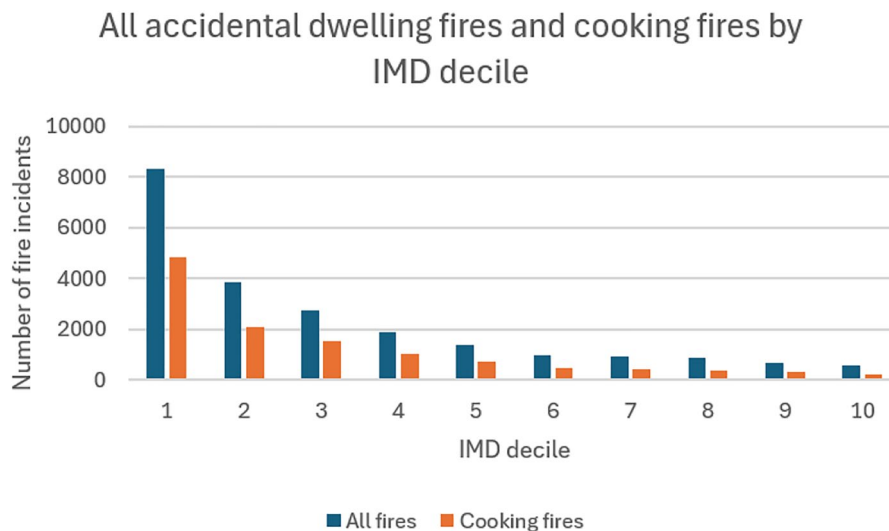


FIGURE 6 | All accidental dwelling fires and cooking fires by IMD decile.

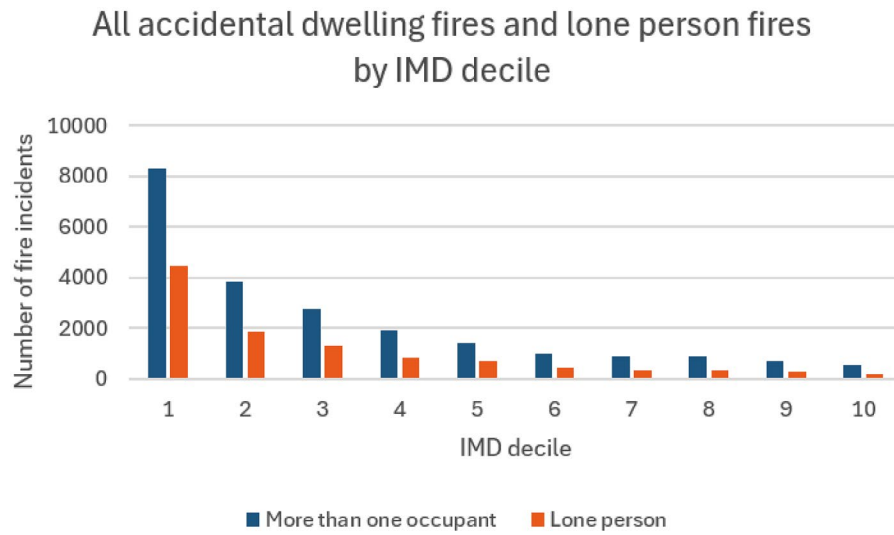


FIGURE 7 | All accidental dwelling fires and lone person accidental dwelling fires by IMD decile.

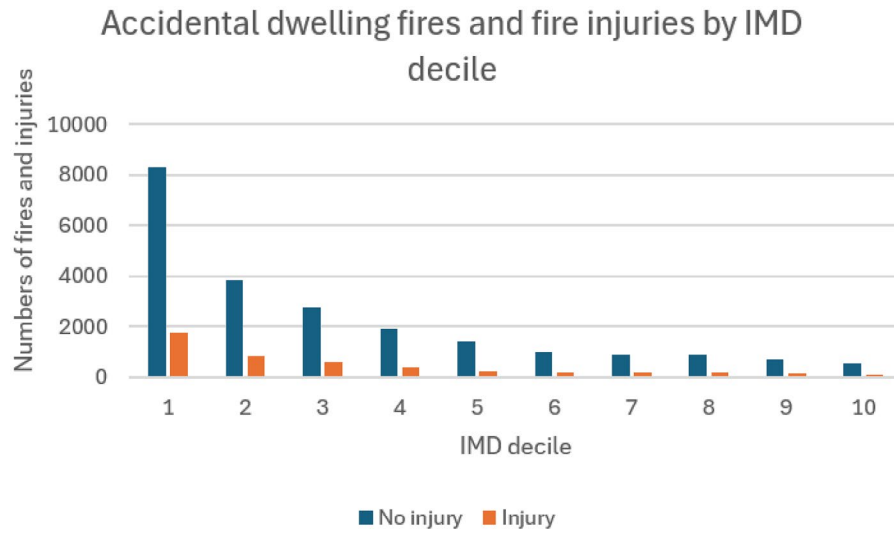


FIGURE 8 | Accidental dwelling fires and fire injuries by IMD decile.

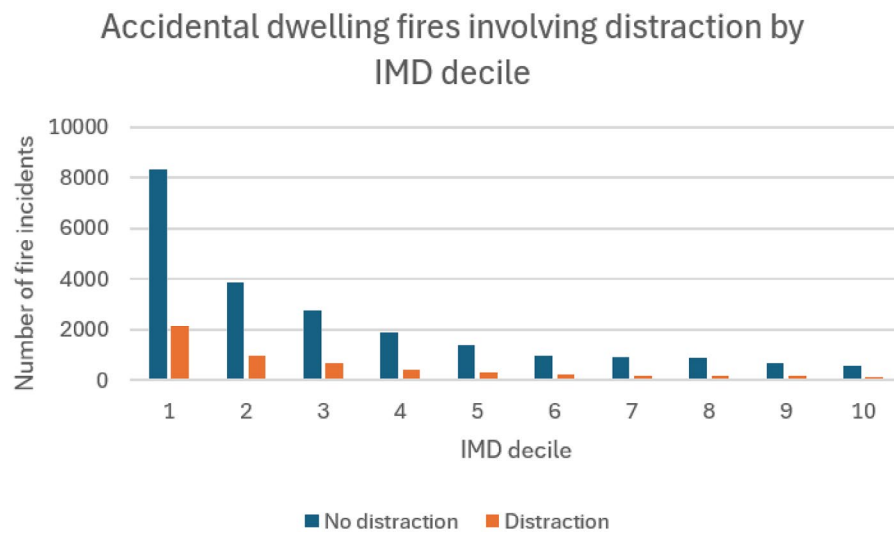


FIGURE 9 | Accidental dwelling fires involving distraction by IMD decile.

fire incidents where both antecedent and consequent occur together. Confidence is the probability of the consequent given the antecedent. Lift compares the rule to random chance. If $\text{Lift} > 1$ this implies that there is a positive association; if $\text{Lift} = 1$ this implies that there is no association; $\text{Lift} < 1$ implies that there is a negative association.

In terms of interpreting the results of the association rule mining from the Greater Manchester accidental dwelling fire dataset, identified patterns included:

14% of the accidental dwelling fire incidents involved both a cooking appliance and IMD decile 1, when a cooking appliance was involved 43% of those incidents occurred in IMD decile 1 areas, this was 14% higher than would be expected if the variables were independent (i.e., the combination occurred about 1.14 times as often as expected by chance alone).

9% of the accidental dwelling fire incidents involved a lone person under pension age and occurred in an IMD decile 1 area, when a lone person under pension age was involved 46% of those incidents occurred in an IMD decile 1 area; this was 23% higher than would be expected if the variables were independent.

10% of the accidental dwelling fire incidents involved both distraction and an IMD decile 1 area; when distraction occurred, 40% of fire incidents occurred in IMD decile 1 areas, and this was 7% higher than would be expected if the variables were independent.

A total of 13% of the accidental dwelling fire incidents involved a cooking appliance and distraction, when a cooking appliance was involved, 38% of fire incidents involved distraction, and this was 60% higher than would be expected if the variables were independent.

Previous research had identified deprivation as a factor in accidental dwelling fire incidence [10, 11] but had not examined the probabilities associated with co-occurrence with other fire risk factors. Previous research had also examined the circumstances relating to accidental dwelling cooking fires [9] but had not examined the probabilities associated with co-occurrence with other fire risk factors. This research extends previous research by examining the probabilities associated with co-occurrence with different fire risk factors.

4.3 | Association Rule Mining for Supporting Accidental Dwelling Fire Prevention

In terms of accidental dwelling fire prevention, overall, the association rules identified in the Greater Manchester dataset indicated that living alone appeared to increase the likelihood of an accidental dwelling fire, as well as living in a deprived area, and that distraction can increase the likelihood of an accidental dwelling fire, especially cooking fires. Previous research had identified that living alone is a common risk factor for accidental dwelling fires [46], that deprivation is a predictor of accidental dwelling fires [10], and that distraction is an issue with regard to cooking fires [47]. This research extended previous research by examining the co-occurrence of different accidental dwelling fire circumstances, and the probabilities associated with such

combinations of circumstances. In particular it appeared that deprivation is a consistent amplifier of fire risk with regard to cooking, distraction, and lone adults under pension age; cooking appliances and distraction form a high-risk behavioral cluster, far above random chance; and younger lone adults in deprived areas are a distinct, under-recognized fire risk group, separate from the usual pension-age focus. These insights can support fire prevention teams identifying precision fire prevention activities. The implications for prevention could include prioritizing Safe and Well visits in deprived areas with high concentrations of cooking-related incidents; working with housing associations in deprived areas to identify households with older or faulty cooking appliances; deploying behavior-specific interventions such as stove timers, induction hob promotion, chip-pan removal, and cooker isolation switches since cooking risk is not evenly distributed, with deprived areas carrying a disproportionate share. In addition, it could be beneficial to target working-age adults living alone, a group often overlooked in fire prevention work. This could involve partnering with job centers, housing support teams, and mental-health services to reach isolated adults, and providing advice regarding the use of low-cost safety equipment such as safer cooking devices. In terms of targeting fires relating to distractions, behavior-specific campaigns could be developed around common distractions including phones, children, caring responsibilities, medication, and alcohol. During Safe and Well visits, targeted questions could be asked regarding routines, multitasking, caring responsibilities, and medication, and landlords could be encouraged to install heat detectors and automatic cooker shut-off devices in high-risk properties.

5 | Discussion

One of the main limitations of the research undertaken was that association rule mining could only be undertaken on data regarding fire incidents attended by Greater Manchester Fire and Rescue Service that were recorded in the fire incident recording system over the time period studied. UK government estimates have indicated that only 25% of domestic dwelling fires are actually reported to a Fire and Rescue Service and recorded in the fire incident recording system [48]. The limitations of association rule mining for accidental dwelling fire incidence analysis are that many rules may be produced that require expert interpretation, the rules are descriptive rather than predictive, the rules require careful pruning to avoid noise, and it is a less familiar data analysis technique for fire and rescue service operational decision-makers compared to geospatial analysis, predictive modeling (such as logistic regression) and risk-scoring frameworks. Association rule mining is transparent in that the rules themselves are easy to read, but the process that generates them is less transparent because it is unsupervised, parameter-sensitive, and produces results that require subjective interpretation. However, association rule mining can still add value as a complementary technique to understand the combinations of circumstances relating to accidental dwelling fire incidence.

6 | Conclusion

The research reported in this paper examined the use of association rule mining for identifying patterns in accidental dwelling

fire incidents attended by Greater Manchester Fire and Rescue Service over the period 2013/14 to 2023/24. In order to utilize association rule mining for accidental dwelling fire analysis it was important to understand the parameters of the Python functions used, and how these controlled the results produced. The `min_support` parameter of the `apriori` function required adjustment to control how frequent an itemset (set of accidental dwelling fire circumstances) must be to be considered frequent in order to filter out sets of accidental dwelling fire circumstances considered too infrequent to be useful, yet retain interesting infrequent patterns. The `min_threshold` parameter of the association rules function controls the minimum value of the chosen metric (such as confidence or lift) that an association rule must meet to be included in the output. Strong predictive reliability can be achieved if a high level of confidence is set, and non-random meaningful associations can be identified if a high level of lift is set. This requires time and effort by fire and rescue service staff to try out different parameters and assess the association rules produced.

Association rule mining requires interpretation of the rules provided by the process in order to determine the most appropriate and useful rules for understanding accidental dwelling fire risk. The higher the confidence level, the greater the predictive reliability of the association rule, and the higher the level of lift, the more likely that the association rule is not due to chance. From the dataset, accidental dwelling fires appeared more likely in deprived areas, and living alone in a deprived area appeared to increase the likelihood of a fire incident. Distraction appeared to substantially increase the risk of cooking fires (60% more likely than chance), and distraction appeared a more common fire incidence factor in deprived areas. Previous research of accidental dwelling fires in the UK found similar results indicating that cooking fires were the most common type of such fires [9] and that deprivation was linked to the likelihood of such fires [10, 11]. This contrasts with the results of association rule mining of structural fires research in Iraq, where electrical fires, fires caused by the carelessness of children, and smokers' materials fires were more common. This difference likely reflects variation in building stock, electrical infrastructure, cooking practices, and fire reporting systems between the two contexts.

This extends previous research into accidental dwelling fire incidence in relation to deprivation and cooking fires by providing the probabilities associated with co-occurrence of different fire risk factors. It is hoped that the analytical process presented in this research may be of use to prevention managers, business intelligence analysts, research and evaluation officers, and other fire and rescue service staff in terms of enabling the analysis of the relationships between different fire risk factors.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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