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Solving the inverse problem of post-mortem interval estimation using Bayesian Belief Networks

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Abstract

Bayesian Belief Networks (BBNs) can be applied to solve inverse problems such as the post-mortem interval (PMI) by a simple and logical graphical representation of conditional dependencies between multiple taphonomic variables and the observable decomposition effect. This study is the first cross-comparison retrospective study of human decomposition across three different geographical regions. To assess the effect of the most influential taphonomic variables on the decomposition rate (as measured by the Total Decomposition Score (TDS)), decomposition data was examined from the Forensic Anthropology Research Facility at the University of Tennessee (n=312), the Allegheny County Office of the Medical Examiner in Pittsburgh, US (n=250), and the Crime Scene Investigation department at Southwest Forensics in the UK (n=81). Two different BBNs for PMI estimations were created from the US and the UK training data. Sensitivity analysis was performed to identify the most influential parameters of TDS variance, with weaker variables (e.g., age, sex, clothing) being excluded during model refinement. The accuracy of the BBNs was then compared by additional validation cases: US (n=28) and UK (n=10). Both models conferred predictive power of the PMI and accounted for the unique combination of taphonomic variables affecting decomposition. Both models had a mean posterior probability of 86% (US) and 81% (UK) in favor of the experimental hypothesis (that the PMI was on, or less than, the prior last known alive date). Neither the US nor the UK datasets represented any cases below 'moderate' support for the value of PMI evidence. By applying coherent probabilistic reasoning to PMI estimations, one logical solution is provided to model the complexities of human decomposition that can quantify the combined effect of several uncertainties surrounding the PMI estimation. This approach communicates the PMI with an associated degree of confidence and provides predictive power on unknown PMI cases.

Key Words

Post-mortem interval, Bayesian Belief Networks, Inverse Problem, Decomposition, Forensic Taphonomy, Taphonomic Variables

Introduction

The importance of estimating the post-mortem interval (PMI) lies within its potential to identify suspects of a homicide offense, substantiate witness statements, assist in identifying the deceased and determine the manner of death [1,2]. In medico-legal death investigations, specialists such as forensic entomologists, pathologists, and anthropologists use various techniques to estimate the PMI, which can corroborate the reported last sighting of the deceased and other available scene evidence [3]. Despite a wealth of experimental research investigating accurate methods of PMI estimation [4-8], PMI estimations are associated with an unquantifiable degree of uncertainty in medico-legal death investigation practice [9]. This is due to the vast array of taphonomic variables that may affect the complex process of human decomposition, where their degree of influence and interrelationships remain uncertain [10-13]. Consequently, PMI uncertainty could mislead the investigation, causing increased pressure on police time and resources [2]. Therein lies the scope to quantify the uncertainty of PMI estimations.

Inverse problems acquire information about a parameter that cannot directly be observed by studying a set of measurements believed to have been caused by the parameter [14]. By this definition, the estimation of the PMI in medico-legal investigations presents itself as an inverse problem. The observed decomposition state is an effect of many potential uncertain variables, of which time and temperature are considered the most influential [4,10]. At the scene of a decomposing body, the PMI (unknown parameter) can be inferred by assessing the decomposition state (known measured effects). Often multiple, and even an infinite number of causes, can explain the observed effect making inverse problems more challenging to solve than their antithesis: the forward problem, which predicts the unknown effects from known cause [15]. As such, forward problems are compatible with experimental research by constructing a working hypothesis to test cause-effect relationships.

Although the PMI is an inverse problem in forensic practice, a compendium of forensic taphonomy research has investigated the PMI as a forward problem. Experimental taphonomic studies using human and non-human analogs utilizing anthropology research facilities have extensively been reported in the literature for several decades [16-20]. Such facilities have enabled the controlled study of soft-tissue decomposition, whereby it has been possible to recreate environmental factors suspected of affecting decay rates and patterns. Ongoing studies in differential decomposition patterns in aquatic [21] and terrestrial [22] environments, as well as recent advances in detecting and differentiating taphonomic agents in soil [23], have slowly developed our knowledge of decomposition processes. However, issues such as small sample sizes, reductionist isolation of taphonomic variables, the restricted application of results to a single geographical region, and significant error rates when attempting to validate PMI estimation models [18,24-27] could explain why no experimentally derived PMI estimation method is neither currently, nor routinely, used in medico-legal death investigation practice.

A forward problem is widely considered to be linear and well-posed if it meets the following three criteria defined by Hadamard [28]: i) existence (the problem has a solution), ii) uniqueness (the solution is unique), and iii) stability (the solution is stable and dependent on the details of the problem). An inverse or ill-posed problem is characterized by its inability to fulfill one or more of the aforementioned requirements. In the case of PMI estimation, the three latter criteria are arguably not met.

The first criterion of Hadamard's [28] requirement for a forward problem is as simple as the problem has a solution. In forensic decomposition cases, the reality presents that unless the death is witnessed or there is irrefutable evidence of the time of death, often the *exact* PMI cannot be solved. Hence, the PMI is often reported as an estimation of the maximum and minimum time intervals between death and the point of the deceased's discovery in police investigations [29]. Interestingly, even under experimental conditions in forensic taphonomy research where the date of death is known, the PMI estimation models based on the observed decomposition state and temperature are still inaccurate, unreliable, and uncertain [26,27,30,31]. This has been attributed to problems inherent within a PMI

model's construction [24,25] and the large array of environmental and intrinsic variables affecting the variability of the decay rate [2,10,12]. Hadamard [28] states that the solution may fail to exist if the observed data is perturbed by noise. This means that solving the exact PMI may not be possible if the observed decomposition characteristics are influenced by the unknown effects of the aforementioned variables. Following the literature consensus that PMI should be reported as a range both in the forensic field [29] and experimentally [4], it is evident that pinpointing a single time since death is challenging. The solution of an exact PMI is often unattainable, which does not align with Hadamard's forward, well-posed problem and further reiterates that the post-mortem interval is an inverse problem.

Hadamard's second property of forward problems is the existence of a unique solution to the problem. Can we exclusively determine the unknown parameters from the observed decomposition measurements? If so, then only one cause will explain most effects. Forensic taphonomy literature has canonized that the PMI will cause an observable decomposition state. On first look, therefore, the 'PMI problem' may appear to fit Hadamard's second criterion. However, a multitude of taphonomic variables can cause a variety of decomposition states on the deceased [12], extending beyond the parameters of a simple cause-effect relationship between time and decomposition. For example, while considered an independent event from the stages of decomposition [32], scavenging inevitably alters the presentation of decomposition on the body, creating further challenges in PMI estimation. Therefore, the 'unknown PMI' cannot uniquely be determined as the sole cause of the observed level of decomposition. While time is largely considered paramount to the decomposition state, it is by no means the only cause of decomposition; hence the solution for PMI is not unique.

Criterion 3 of Hadamard's forward problem is a question of stability, requiring that small changes to the cause of the problem do not produce large changes to the output or solution. Translating this to PMI estimations, we may ask, will small changes to the cause of our decomposition observations (time, temperature, etc.) produce large changes to the effects: the decomposition state itself. Invariably the answer is yes. Given that over a decade of forensic taphonomy research has devised different time-dependent stages of decomposition [4,5,11], it is logically concluded that the solution of PMI is unstable. This means that small changes to the multiple causes and variables of the decomposition state (e.g., time and temperature) cause significant effects on the pattern and rate of decomposition. While there may be some exceptions to this (e.g., where the effect of time on decay is negligible in the imposed 'static' state of mummification [33]), the majority of research implies that early to moderate decomposition states are primarily time-dependent [4,10,13]. Furthermore, the existence of differential decomposition, whereby anatomical regions may simultaneously display different decay states, only exemplifies the instability of the 'PMI problem.'

A wealth of research has attempted to quantify the uncertainty surrounding PMI estimations using linear regression analysis and confidence intervals [4,26,27,34,35]. However, fundamental flaws have been identified with such frequentist inferences since they do not quantify what is known about the PMI parameter [25,36]. Put simply, an accurate PMI estimation within the 95% confidence interval does not mean a 95% probability of finding the true PMI in an unknown case. Given that PMI estimations are characteristic of an inverse problem, it is arguable that they should be subject to statistical methods designed to solve such problems.

Bayesian Belief Networks (BBNs) are a powerful tool to solve inverse problems by simple and logical graphical representation of conditional dependencies between multiple variables and the observable effect. Since the late 1908s, BBNs have found wide-reaching applications in forensic science, including DNA, trace evidence transfer, mass spectroscopy, and the field of forensic anthropology [37-39]. BBNs are communicated via likelihood ratios that express the evidence's strength or value for or against a given hypothesis. In the case of PMI estimation, there have been a few attempts to devise BBNs using rectal temperature data [40,41], forensic entomology [42], and indoor decomposition cases [36].

The main aim of this study was to develop and compare the accuracy of two different BBNs for PMI estimations in UK and US medico-legal death investigations. In creating these models, the secondary aim was to assess the most influential taphonomic variables of the decomposition rate by engaging a control dataset of experimental cadavers from an Anthropology Research Facility (ARF) in Tennessee to compare UK and US decomposition cases. To the authors' knowledge, this is the first cross-comparison study of decomposition across three geographical regions and the first creation of a BBN that accounts for the dominance of taphonomic variables and overall PMI uncertainty.

Materials and Method

Control Data

Before creating the UK and US BBN, a control dataset was required to generate a probability density function of the independent variables PMI and accumulated degree-days (ADD) on the total decomposition score (TDS) dependent variable. This aided understanding of how time and temperature affect accumulated decomposition. Notably, the control dataset facilitated the daily recording of ADDs and decomposition from fresh to skeletonization at known PMIs. This is simply not possible in retrospective case studies of decomposition where only a 'snapshot' of the decay is presented upon discovery of the deceased.

It was important to ensure 'standardization' of taphonomic variables in the control data to assess the effect of temperature and PMI on the rate and pattern of decomposition. The control dataset comprised 8 adult cases (4 male, 4 female) between 57 to 65 years old from the University of Tennessee's Body Donation Program examined at the Anthropology Research Facility (ARF) in Knoxville, Tennessee, US. The ARF is approximately 3 acres of densely populated deciduous woodland enclosed by razor-wire fencing on the Tennessee River's south bank.

The cadavers were stored in a 3°C morgue cooler for no less than 24h to equilibrize internal body temperature before being placed in a supine position on clean ground in individual plots. The plots were approximately 20m apart, and cadavers had little exposure to direct sunlight under the dense canopy cover of maple, oak, and hickory trees. All 8 cadavers represented natural causes of death and were left unclothed and uncovered.

Training Data

To create Bayesian Belief Networks (BBNs) of PMI estimation, training datasets of known PMI were required from the United States (US) and the United Kingdom (UK). Retrospective cases of decomposition were collected from the Allegheny County Office of the Medical Examiner (ACOME) in Pittsburgh, Pennsylvania, and Southwest Forensics (SWF), a collaboration of 4 police forces across the southwest region of the UK (Wiltshire, Dorset, Avon and Somerset, and Devon and Cornwall).

Allegheny County Office of the Medical Examiner (ACOME)

The ACOME provides medico-legal death investigation for sudden, unexplained, and unnatural deaths across Allegheny County in Pittsburgh [44]. After being notified of a death by the Emergency Medical Service (EMS) or police; the forensic investigators (FI) gather detailed information on the circumstances surrounding the death (e.g., medical history, body condition, and demographic data) to triage cases that fall under the jurisdiction of the Medical Examiner [44]. The FIs then attend the scene to conduct a further investigation with law enforcement. This includes scene and evidence documentation with photography, establishing the deceased's identity, and analyzing the body's condition in-situ, including evaluating post-mortem changes and traumatic injuries.

Case information was extracted from death investigation reports stored in the ACOME Medical Examiner's Information Management System (MEIMS). The death investigation reports are completed by the FIs and contain four sections. The first section is a 'general death information' form of demographic data, medical history, and the official time of death that is recorded upon initial notification of the death by the Emergency Medical Services (EMS) or police. The second section requires a 'report of the scene investigation,' including the location of death, body position, ambient temperature, and presence of rigor mortis following the FI scene attendance. The third section consists of 'body intake information' (e.g., weight and height of the deceased). The final section is a free-text narrative of contemporaneous scene observations, including circumstantial and contextual information of the death, the identification of the deceased, and an analysis of the body in-situ (evaluation of post-mortem changes and traumatic injuries). Importantly, this section details the reported PMI (calculated as the number of whole days between death and discovery) and the origin, or source, of this information.

Southwest Forensics

In the UK, decomposition cases were collected retrospectively from the Crime Scene Investigation (CSI) department in Southwest Forensics (SWF), a collaboration of 4 police forces across the southwest region: Wiltshire, Dorset, Devon and Cornwall, and Avon and Somerset. CSI will be notified of an unexplained or sudden death via the central control room or by the first attending officer (FAO). The CSI will then attend the scene, usually accompanied by an officer from the Criminal Investigation Department (CID). The CSI will be responsible for scene and evidence documentation through photography and scene notes and will assist CID in ruling out any suspicious or third-party involvement.

The CSI departments utilize a forensic case management system, Socrates [45], which was centralized across SWF in 2015 to facilitate crime scene data sharing between the four geographical regions. Socrates facilitates recording demographic data related to the case and contains a free-text section for CSI scene notes. In relation to decomposition cases, the free-text section is where reported PMI information is contained along with contextual crime scene examination notes, which detailed various taphonomic variables.

Sample Selection

A total of 2,332 adult decomposition cases were available for analysis when combining the US and UK datasets (Figure 1). In the US, decomposition cases were extracted retrospectively from ACOME's MEIMS over 10 years between 2007 to 2016 (n=2074). Each decomposition case had a one-word descriptor of the decay level pre-assigned by autopsy technicians in consultation with forensic pathologists. This included the following codes: 'early decomposition,' 'moderate decomposition,' 'advanced decomposition,' 'mummification,' and 'skeletonization.'

The remaining cases were collected retrospectively from SWF CSI between 2015 to 2019 (n=258). The decomposition stage was taken from the CSI scene notes and confirmed by viewing the scene/and or post-mortem photographs. For consistency across the datasets, the same aforementioned decomposition codes were used. For example, if scene notes stated, 'skin slippage,' this was assigned 'early decomposition' as per the canonized stages of decomposition in forensic taphonomy literature [4,11].

This study aimed to create and compare two environmentally different BBNs of PMI estimation. The minimum sample inclusion required a known PMI and details of the origin of the PMI information source. Previous research suggests that only reliable PMI sources (e.g., digital communications, CCTV, forensic specialists, witnessed deaths, and missing person reports) should be included when creating PMI estimation models [24,46]. Therefore, only cases with the aforementioned reliable PMI sources were included in this study.

In ACOME, 1,714 cases had a reported PMI, compared to 188 cases in SWF. Cases with unknown PMI were first excluded from both datasets (ACOME n=297, SWF n=53) (Figure 1). Cases with an unreliable PMI were also excluded (ACOME n=1,436, SWF n=97). As the Total Decomposition Scoring (TDS) method was used to record the accumulated decomposition level, water-context deaths and drowning cases were excluded since the TDS system is unsuitable for use on water-based deaths [5]. Therefore, the final sample comprised 278 cases for the ACOME and 91 cases for SWF, all of which had a reliable PMI (Figure 1). Approximately 10% of these samples were required to validate the BBNs. This resulted in 28 validation cases for the ACOME and 10 for SWF. The training dataset, therefore, consisted of 250 cases for ACOME and 81 cases for SWF.

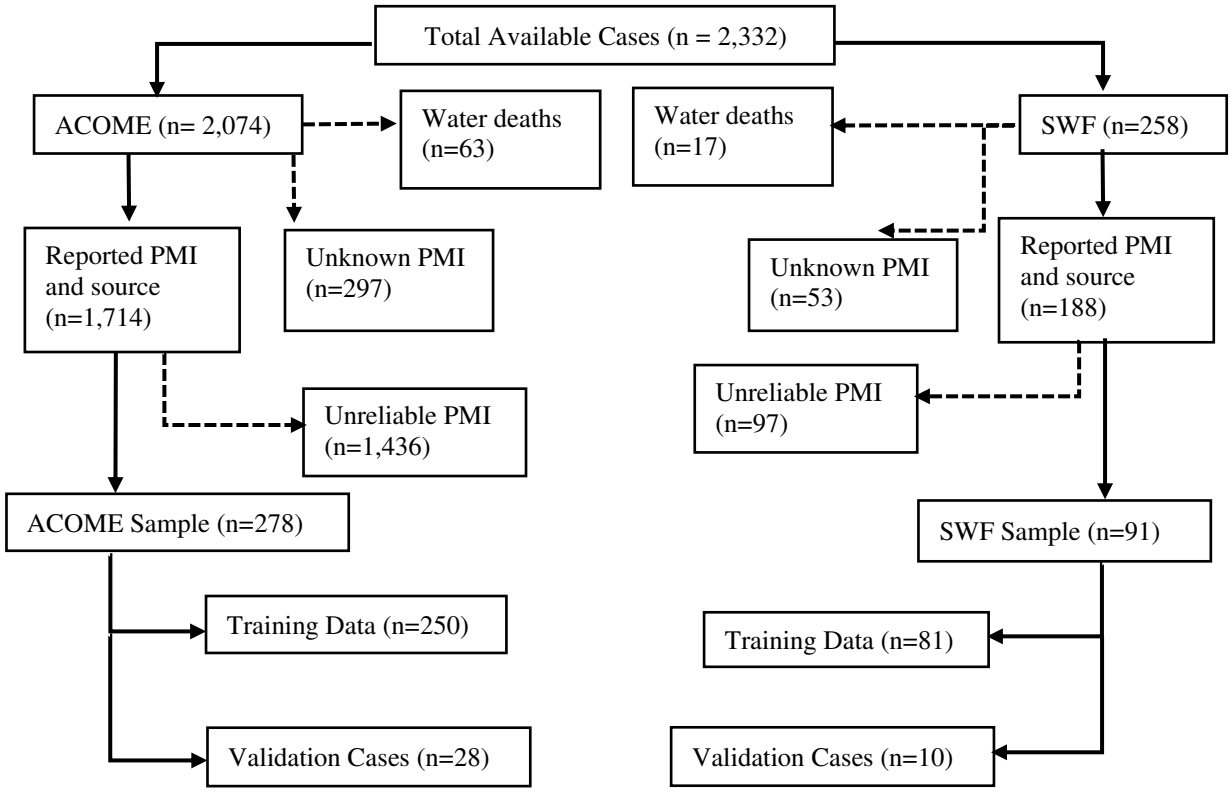

Figure 1. ACOME and SWF Decomposition Case Selection (dashed lines represent excluded cases)

Recording Decomposition and ADD

In both ACOME and SWF, decomposition was recorded from the crime scene photographs following recent research that has shown post-mortem decomposition can accelerate in mortuary storage temperatures, affecting the interpretation of the estimated PMI [2]. In the control dataset, decomposition was scored on-site every day between 1 and 30 days, then at 35, 50, 50, 60, 70, 80, 90, and 100 days. This resulted in 312 independent observations.

The Gelderman et al. [5] total decomposition scoring (TDS) method was used to score the decomposition state across three anatomical regions of the body: facial decomposition score (FDS), body decomposition score (BDS), and limbs decomposition score (LDS). Each anatomical region comprises a six-point scale ranging from a score of 1 (no visible changes) to 6 (complete skeletonization), and the scores are then summed to obtain a total decomposition score (TDS) that reflects the overall level of decomposition. Unlike other decomposition models for humans [4], the TDS method does not assume a rigid sequential order of decomposition characteristics. It provides greater flexibility in assigning points that comprise multiple decomposition descriptors by using terminology

such as ‘skin slippage and/or marbling’’, meaning they need not all be present to assign the anatomical score.

The TDS system was used in descending order to score cases. This meant that all cases started with a score of 6 in each anatomical region (complete skeletonization), and points were deducted if the descending decomposition criteria were absent. When the first criterion was present, the corresponding class score was assigned. For example, if a body presented 'skin having a leathery appearance,' the BDS started at 6 (complete skeletonization) until this characteristic was visible in the BDS criteria (4.2). The case would then be assigned a BDS of 4. This approach was taken to avoid bias in ascending scoring, where more advanced characteristics could be missed if the scoring stopped at the first criterion visible in the photographs.

Since the PMI estimation was derived from the BBNs, the ADD and the PMI were *not* estimated using the proposed Gelderman formula; only the actual ADD was calculated. The actual ADD was calculated each day from an on-site daily temperature logger at the ARF by dividing the sum of the maximum and minimum air temperature by two. The mean temperature values were then summed for each PMI day. For example, if the mean air temperature was 8°C on PMI day 1 and 9°C on PMI day 2, the ADD is 8 for day 1 and 17 for day 2. For the ACOME and SWF data, the ADD was calculated using the same formula, and the mean daily temperatures were summed for the duration of known PMI days. The ambient indoor temperature was recorded for indoor deaths at the time of discovery. Given that indoor temperatures are less subject to extreme fluctuations than outdoor temperatures, it was assumed that bodies were exposed to this temperature for the duration of the PMI. For outdoor cases, the mean daily temperatures were taken from the nearest weather station for land deaths.

Taphonomic Variables

Taphonomic variables were recorded from the death investigation case notes for the ACOME and SWF datasets (Table 1). Intrinsic variables were characterized by the sample's demographics and internal factors that varied between individuals. Scene variables related the body to the scene's context, and extrinsic variables comprised environmental factors that could influence the decomposition state. The control dataset only had ADD, TDS and the temperature recorded for the duration of the 100-day study since all other taphonomic variables remained constant.

	Taphonomic Variable	**Description**
Intrinsic	Age	Recorded age at death.
	Sex	Recorded as male or female.
	Weight (pounds)	Recorded weight at autopsy examination.
	Height (inches)	Recorded height at autopsy examination.
	Body mass index (BMI)	Calculated at the post-mortem examination as: BMI = body weight/height ^{squared} Classified as follows: Underweight (<18.5), normal (18.5 to <25), overweight (25 to <30), class I obesity (30 to <35), class II obesity (35 to <40), class III obesity (>40).
	Cause of death	There are an infinite number of causes of death determined by the forensic pathologist.
	Manner of death	ACOME pathologists can assign one of five manners of death: natural, accidental, suicide, homicide, or undetermined [44].
Scene	Death location	Recorded as indoors, outdoors (surface depositions), or inside a vehicle.
	Body Position	Recorded as supine, prone, lateral, kneeling, seated, or suspended.
	Clothing	Recorded as fully clothed, partially clothed, unclothed, and covered (e.g., bedding material).
	Decomposition Stage	A one-word descriptor of the decomposition stage: early, moderate, advanced, mummification, skeletonization. In the ACOME, this was pre-assigned by autopsy technicians. In SWF, this information was extracted from the CSI scene notes.

Environmental	Temperature	Recorded at the scene by medico-legal death investigators or CSI. For indoor cases, a single thermostat reading was taken within the residence or by using a portable ambient air thermometer (for vehicle cases). The mean daily temperature was recorded using data from the nearest location weather station for outdoor cases. In all cases, the temperature readings were recorded by photographs at the start of the investigation.
	Season	Meteorological seasons were recorded as winter (December, January, February), spring (March, April, May), summer (June, July, August), and autumn (September, October, November).

Table 1. Recorded taphonomic variables for the SWF and ACOME datasets.

Statistical Analysis

All statistical analysis was conducted using EXCEL XLSTAT software (version 2020.5.1). The PMI (in days) and ADD were treated as independent, discrete variables where an exact value of the variable can be identified (e.g., PMI 1, ADD 240). The TDS was also defined as a discrete, categorical variable but was treated as a dependent variable since it is subject to both time and temperature effects.

Probability distribution function (PDF) defines the probability distribution of a discrete random variable. It is commonly employed to find the probability distribution of data and depends upon calculating the mean and standard deviation of the dataset. PDF plots were created to show the probability distribution of the dependent variable (TDS) by the independent variables of PMI and ADD for the control dataset only. The specified mean and standard deviation of the independent variables were calculated according to the TDS. Since TDS can take values from 3 to 18, PDFs were created for only select, representative TDS of 6, 9, 12, 15, and 18. The TDS curves were then compared between different PMI and ADD days to measure the effect of these variables on the accumulated decomposition. PDFs perform best with large datasets and were, therefore, created for the control dataset due to the high frequency of sequential observations of 8 bodies between 1 and 100 PMI days (n=312). However, simple probability distribution graphs were created for the US, UK, and control datasets to compare the probability of the PMI, TDS, ADD, and temperature variables. Two-sample t-tests were then used to test for significant differences in the PMI values associated with the TDS and ADD between the three datasets. The creation of the PMI probability in the US and UK training datasets was necessary to calculate the value of evidence from the derived BBNs.

Excess kurtosis was calculated as a statistical measure of curve skewness and to describe the distribution tails, which indicate the density of outliers relative to the mean of the probability distribution [47]. Excess kurtosis values can range from -3 (a platykurtic distribution with fewer and 'less extreme' outliers) to infinitely positive (a leptokurtic distribution characterized by more and 'greater extreme' outliers) when compared to the normal distribution, which has a kurtosis of 0.

Bayesian Belief Networks

Bayesian Belief Networks (BBNs) were created for the US (n=250) and the UK (n=81) training datasets using the PC search algorithm in Genie 3.0 Academic [48]. BBNs are directed acyclic graphs (DAGs), which model joint probability distributions according to the inputted taphonomic variables (Table 1). While there are various types of nodes, each node must have a minimum of two states and must contain only nominal, discrete, or interval data. The chance nodes are determined by the conditional probability of state x, based on the combination of states in the parent nodes. The relationship between parent and child nodes is represented by influence arcs (arrows). Upon entering the observed taphonomic evidence of an unknown PMI case, the BBN is automatically updated, and the PMI (parameter of interest) will contain the posterior probability distribution of the PMI.

Sensitivity analysis was first performed to quantify the influence of the taphonomic variables (Table 1) on the TDS, which subsequently influences the posterior probability distribution of the PMI. The Genie 3.0 Academic software incorporates sensitivity analysis in the form of a developed algorithm [49] which calculates a set of derivatives of each parameter in the BBN over specified target nodes (*t)*. This facilitated refinement of the model by identifying and comparing the most important parameters influencing the TDS target node *(t)*. The results of the sensitivity analysis are communicated in numerical values between 0.00 (no influence) – 1.00 (maximum influence) [48]. If the derivate is large for a node (*n*), then a small change in (n) may lead to a large change in the posterior distribution of the target node (*t*), and the taphonomic variable was deemed important. Conversely, if the derivate is small, then large changes have little to no effect on the posterior distribution of *(t),* providing rationale for excluding the specified node. Taphonomic variables were only removed from the BBN if their influence on the TDS was redundant (defined as 0.00 numerical derivative) to improve the model accuracy [50].

The US and UK BBNs were then validated by inputting the taphonomic variables of the 28 US and 10 UK cases. The validation cases had a 'blind' PMI unknown to the researchers. The last known alive information (LKA) in days of the validation cases was inputted as the prior evidence (along with the other taphonomic variables). This facilitated the formulation of two hypotheses to estimate the PMI. The experimental hypothesis (HExp) was defined as the probability of the PMI being less than or equal to x number of days (PMIx), as defined by the LKA information. The null hypothesis (HNull) was defined as the probability of the PMI being greater than x number of days (PMIx), as defined by the LKA information. The evidence (E) represented the conditional probabilities of the taphonomic variables for the case in question.

The application of Bayes theorem to the PMI estimation can therefore be expressed in the following Bayes factor equation:

$$P(PMIx) = \frac{(P(HExp \mid E)) / (P(HNull \mid E))}{P(HExp) / P(HNull)}$$

The Bayes factor is defined as the likelihood of HExp to the likelihood of HNull and facilitated the quantification of the value of evidence (v), i.e., that the PMI was x number of days. The value of evidence (v) was then translated into qualitative terms to express the strength of the influence (Table 2).

V Intervals	Interpretation
1 < V < 10	Limited support
10 < V < 100	Moderate support
100 < V < 1000	Moderate-strong support
1000 < V < 10000	Strong support
> 10000	Very strong support

Table 2. Scale of conclusions for the value of evidence. Adapted from Everett [51]

The qualitative expression of the value of evidence facilitated a comparison of the UK and US BBNs' strength of their predictive PMI capabilities. Two sample t-tests were also used to test for statistical differences in the value of evidence between the US and UK BBNs.

Results

Sample Observations: PMI, TDS, ADD, and Temperature

The UK had a higher mean PMI of 48 days (SD ± 86) and longer PMI range (1 to 575 days) than the US, which conferred a mean PMI of 11 days (SD ±22) and shorter PMI range (1 to 300 days). Approximately 84% of US cases fell between 1 to 14 PMI days (n=209) compared to 48% of UK cases

(n=39). The frequency of cases beyond 21 PMI days declined for both datasets. In the UK, 31% of cases represented longer PMIs (>21 days) (n=38), compared to only 10% of US cases (n=25). It was not possible to calculate a mean PMI for the control since this consisted of 8 cases observed daily between 1 to 30 days, every 5 days between 35 to 50 days, and every 10 days between 50 to 100 days.

The TDS for the control dataset ranged from 6 (livor mortis, rigor mortis) to 18 (complete skeletonization), with a mean of 11 TDS (SD ±4, n=312 observations). The UK TDS ranged from 5 to 18 and had a mean TDS of 10 (SD ±3, n=250). The US dataset represented every possible TDS and ranged from 3 (no visible changes) to 18 (complete skeletonization) and conferred the overall lowest mean TDS of 8 (SD ±2, n=81). In the US, 80% of cases fell between a TDS of 6 and 9 (n=199), compared to 47% of the UK sample (n=38) and 45% of the control sample (n=139). The control dataset had 50% of cases representing a higher TDS of 12 to 18 (n=154), compared to 27% of UK cases (n=22) and just 7% of the US dataset (n=17). In the control dataset, TDS of 8, 11, and 17 represented the lowest frequencies. Since the TDS was measured daily in the control dataset, bodies representing these scores did so for only a short duration (e.g., only 1 to 2 days) before quickly progressing to a higher TDS.

The UK had the highest mean ADD of 881 (SD ±1576) and the longest ADD range (4 to 10,350), whereas the US had the lowest mean ADD of 215 (SD ±485) and a shorter ADD range (0 to 6,600). The control dataset had the shortest ADD range of 2 to 2517 ADD, with a mean ADD of 494 (SD ±505, n=312). In the US, most cases had ADD values ranging from 0 to 500 (92%, n=230), compared to 64% of UK cases (n=52) over the latter ADD range. The control dataset had the greatest frequency of observations, around 101 to 800 ADD (56%, n=175), with no observations beyond 3000 ADD. The UK had the greatest frequency of cases between longer ADD ranges of 801 to >3000 (28%, n=23), compared to the US (2%, n=6) and the control (18%, n=56) over the latter ADD range.

The UK had the lowest mean scene temperature of 19°C (SD ±5°C) and the shortest recorded temperature range (3°C – 29°C), whereas the US had the highest mean scene temperature of 21°C (SD ±6°C) with a broader temperature range from -5°C - 35°C. Conversely, the control dataset had a mean temperature of 20°C (SD ±10°C) and a comparable wide temperature range recorded (-8°C - 32°C). The control dataset had two high peaks of both low and high temperature recorded at 2°C (n=16) and 28°C (n=33), which is reflective of the extreme fluctuating temperature across the distinct Tennessee seasons. In the UK, 72% of cases fell between the 15 to 22°C temperature range (n=58), whereas 70% of US cases fell between the higher temperature range of 19 to 25°C (n=173).

Probability Distribution Function: TDS and PMI

As the PMI increased, the TDS also progressed in sequence across all datasets. At a TDS of 6 (representing the early stage of decomposition), the mean PMI was comparable between the UK (3 US ± 2), the US (4 days, SD ± 2), and the control (5 days, SD ± 5) ($p>0.05$). The UK also had the shortest mean PMI for TDS 9 (9 days, SD ±6) compared to the US (12 days, SD ±1) and the control (13 days, SD ± 7). However, there were no statistical differences in the PMI associated with TDS 9 between all datasets ($p>0.05$).

The control had the fastest rate of decay as a TDS of 18 (complete skeletonization), which was reached at a mean of 76 PMI days (SD ± 19), whereas the UK had the slowest rate of decay with TDS 18 occurring at a mean PMI of 470 days (SD ± 105). A two-sample t-test revealed statistically significant differences in the PMI associated with a TDS of 18 between the UK (n=2) and the control (n=29) ($p<0.05$). In comparison, cases in the US dataset reached skeletonization (TDS 18) at a mean of 131 days (SD ± 102). The UK also had statistically longer mean PMIs for TDS 12 (60 days, SD ± 52) and TDS 15 (109 days, SD ± 94), compared to the US equivalent of 19 days (SD± 1, TDS 12) and 27 days (SD ± 39, TDS 15) and the control of 26 days (SD ± 18, TDS 12) and 40 days (SD ± 19, TDS 15) (p

<0.05). There were no statistical differences in the mean PMI for TDS 12, 15, and 18 between the US and the control (p>0.05).

Figure 2 presents the probability distribution of the PMI for selected TDS created using the mean PMIs and associated standard deviations. Asymmetrical and positively skewed curves were present in the control dataset for all selected TDS except for TDS 18 (complete skeletonization) (Figure 2). For TDS 6, 9, 12, and 15, a boundary was imposed on the left-hand side of the graph where PMI values were clustered, typical of positively skewed distributions. The minimum PMI for the TDS 18 curve was 25 days; hence the absence of this boundary for TDS 18

The curves for TDS 6 and 9 represented leptokurtic distributions since they had a higher density of cases surrounding the mean PMI of 5 and 13, respectively, with less variability in the PMI (Figure 2). This was further supported by the positive excess kurtosis values of 1.1 (TDS 6) and 0.2 (TDS 9). Conversely, TDS 12, 15, and 18 represented platykurtic distributions, representing greater PMI variability and fewer cases clustered around the mean PMI for each curve. The negative excess kurtosis of -0.1 (TDS 12), -1.1 (TDS 15) and -3.9 (TDS 18) confirmed the platykurtic distributions.

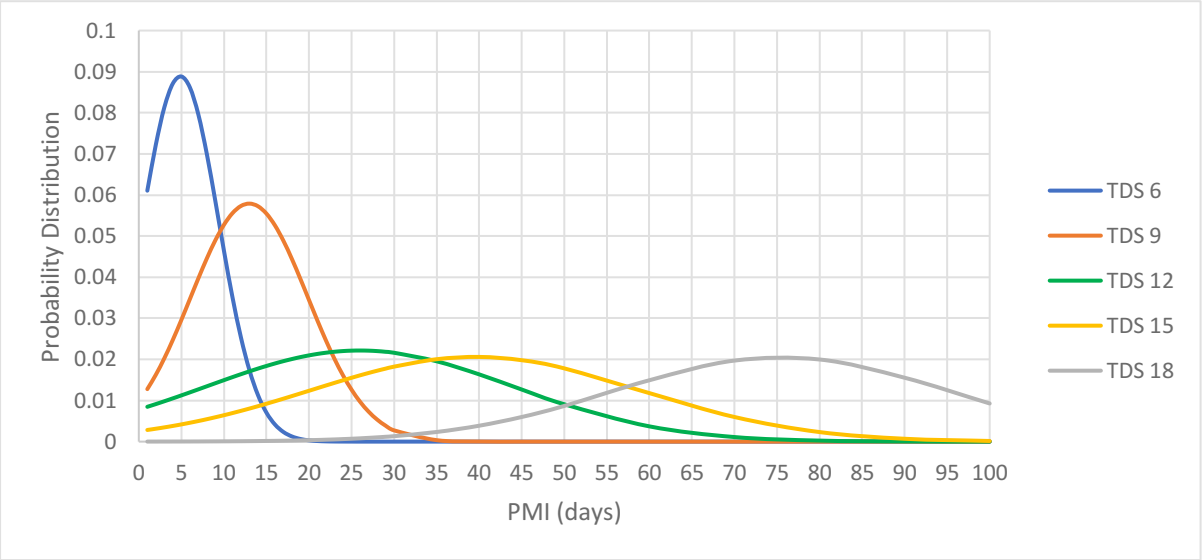

Figure 2 Probability Distribution Plot of select TDS by the PMI in days for the control dataset (n=312 observations).

Probability Density Function: ADD and TDS

Overall, the mean ADD increased with TDS progression for each dataset. ADD measures the passage of time and temperature by summing daily average temperatures the bodies were exposed to from death to discovery.

The control had the lowest mean ADD of 29 ADD days (SD ±17) for a TDS of 6, which was significantly different from the UK (46 ADD, SD ±28) and the US (54 ADD, SD ±51) at TDS 6. In the UK, a TDS of 9 was reached at the lowest mean ADD of 173 (SD ±92), compared to the US (251 ADD, SD ±229) and the control (245 ADD, SD ±131), albeit these differences were insignificant (p>0.05).

As the TDS progressed, the UK had the highest mean ADD for TDS 12 (1233 ADD, SD ±1175) and TDS 15 (1415, SD ±1261), compared to the US equivalent: 439 ADD (SD ±385, TDS 12) and 676 ADD (SD ±269, TDS 15) and the control 586 ADD (SD ±282, TDS 12) and 904 ADD (SD ±487, TDS 15). However, statistical differences in the ADD values of TDS 12 and TDS 15 were only present between the US and UK datasets (p<0.05). In the control dataset, TDS 18 was reached at the lowest

mean ADD of 1634 (SD ±535) compared to the UK (7815 ADD, SD ±2535) and the US (2877 ADD, SD ±2254), with statistical significance found between these differences ($p<0.05$).

The probability distribution plot for the selected TDS by the PMI represented asymmetrical and positively skewed curves in the control dataset for all selected TDS except for TDS 18 (complete skeletonization) (Figure 3).

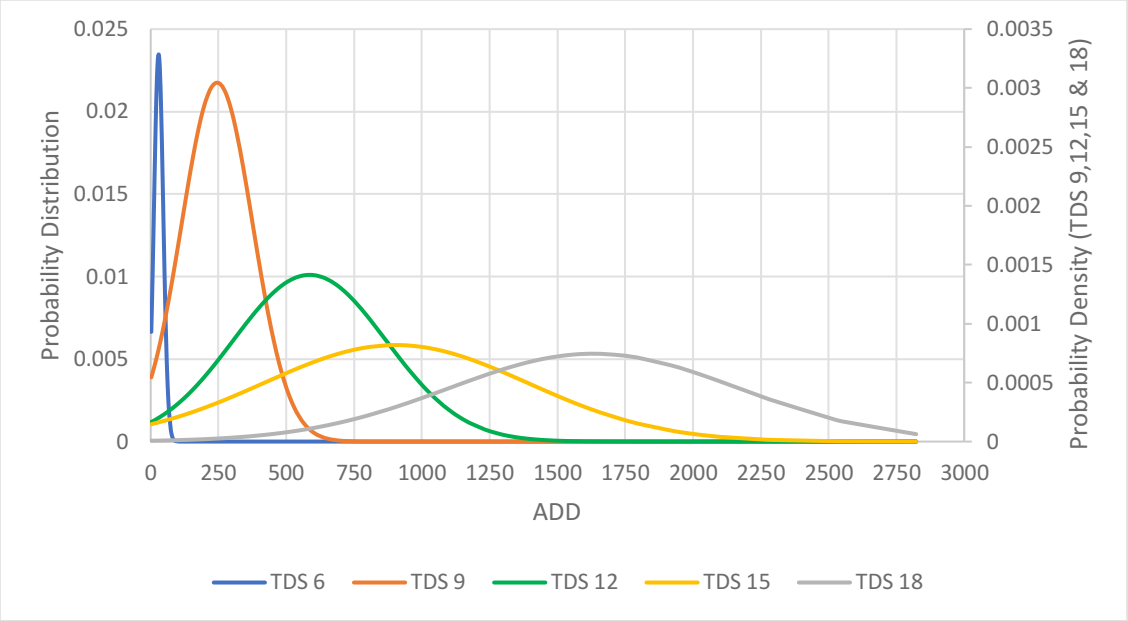

Figure 3 Probability Distribution Plot of select TDS by the ADD for the control dataset (n=312 observations). The primary y-axis represents only TDS 6, as a secondary y-axis was created to scale the TDS of 9,12,15, and 18.

Similar to the mean PMI, the ADD increased as the TDS progressed, with higher TDS associated with higher ADD values (Figure 3). TDS 6 represented a leptokurtic distribution with a higher density of cases surrounding the mean ADD of 29 and positive excess kurtosis of 5.06. The remaining TDS curves 9 to 18 represented a platykurtic distribution with wide variability in the PMI and negative excess kurtosis values ranging from -0.83 (TDS 9) to -2.1 (TDS 18).

Sensitivity Analysis

Bayesian Belief Networks (BBNs) were created for the US (n=250) and the UK (n=81) training datasets using all taphonomic variables. A summary of the node states for each BBN in the UK and US models are presented in Table 3. The results of the sensitivity analysis showed that the PMI was the most influential variable of TDS in both the UK (0.74) and the US (0.86) (Table 3). Age, sex, and clothing had computed derivates of 0.00, indicating that large changes in the individual states of these nodes produced no effect on the probability distribution of the TDS. These redundant variables were therefore excluded from both the UK and US BBN. In addition, the UK model also excluded BMI, temperature, and season due to the 0.00 derivative values. Conversely, BMI (0.24), temperature (0.37), and season (0.71) had a strong influence on the TDS in the US model. ADD was also more influential in the US (0.44) compared to the UK (0.06). For the remaining taphonomic variables, the US had higher derivative values than the UK, except for the manner of death, which conferred a stronger influence over TDS in the UK (0.58) than the US (0.44).

Bayesian Belief Networks

The US and UK Bayesian Belief Networks (BBNs) are presented in Figures 4 and 5, respectively. The taphonomic variables in the BBN are displayed as parent and child nodes. For example, the ‘cause of

death' is the child node of both 'death location' and 'manner of death' and also the parent node to 'body position.' The directional arrows (or arcs) correspond to the causal relationship between the taphonomic variables, meaning the node at the arc's tail influences the node's probability distribution at the arc's head. The nodes can also be displayed as 'bar charts' (an example is provided in Figure 5), which show the posterior probability distribution of the variable, or in the case of the example, the result of inputting a specific state of that variable (e.g., selecting 'suicide'). A multitude of variables influence the TDS (including PMI). The posterior probability distribution of the PMI can be read in the yellow node and will be updated based on the conditional probabilities of the other taphonomic variables inputted that affect TDS. The US and UK BBNs used the same parent and child nodes, except for BMI, season, and temperature, which were excluded from the UK BBN due to their weak relationship with TDS as determined by the sensitivity analysis (Table 3).

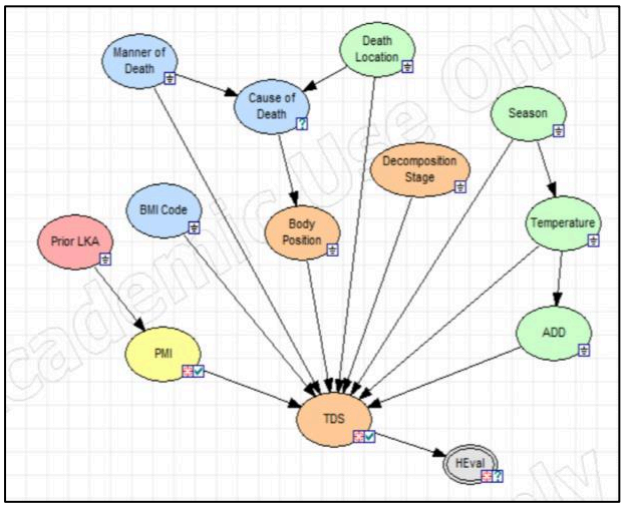

Figure 4 - Bayesian Belief Network for PMI Estimation in the US (n=250). Node Colour Key: blue = intrinsic variables, orange = scene variables, green = environmental variables, yellow = parameter of interest, red = prior last known alive (LKA) information, grey = output hypothesis.

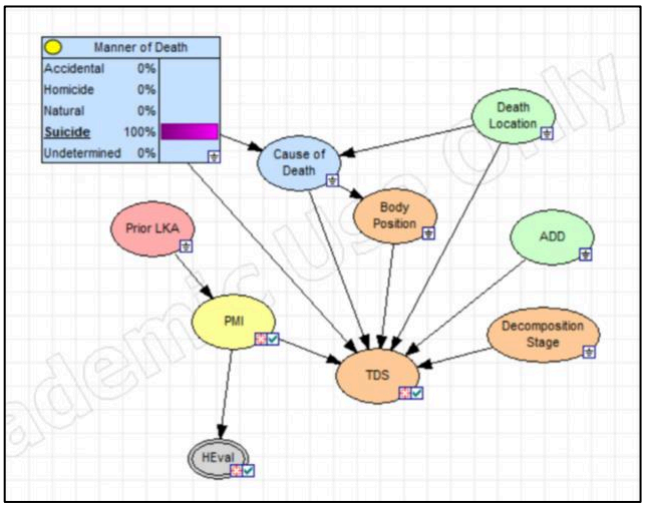

Figure 5 - Bayesian Belief Network for PMI Estimation in the UK (n=81). Node Colour Key: blue = intrinsic variables, orange = scene variables, green = environmental variables, yellow = parameter of interest, red = prior last known alive (LKA) information, grey = output hypothesis.

Parameter	Description	Data	Node	Node Sensitivity Analysis		Node States	
				UK	US	UK (n=78)	US (n=250)
PMI	Estimated post-mortem interval (days)	Interval	Chance	0.74	0.86	PMI days: 1 to 8 inclusive, 10, 12, 14, 15, 16, 19, 20, 21, 22 to 25, 26 to 30, 31 to 35, 36 to 40, 41 to 50, 51 to 60, 61 to 80, 81 to 100, 101 to 150, 151 to 200, 201 to 300, >300.	PMI days: 1 to 21 inclusive, 22 to 25, 26 to 30, 31 to 35, 36 to 40, 41 to 50, 51 to 60, 61 to 80, 81 to 100, 101 to 150, 151 to 200, 201 to 300, >300
Prior LKA	Prior last known alive information (days)	Interval	Chance	N/A	N/A	As above	As above
HEval	Hypothesis evaluation	Binary	Deterministic	N/A	N/A	0 – if the PMI is lower than the prior LKA value 1 – if the PMI is higher than the prior LKA value	
TDS	Total Decomposition Score	Discrete	Chance	N/A	N/A	TDS 5,6,7,8,9,10,11,12,13,14,15,16,18	TDS 3 to 18 inclusive
ADD	Accumulated Degree days	Interval	Chance	0.06	0.44	ADD value ranges: 1 to 10, 11 to 20, 21 to 30, 31 to 40, 41 to 60, 61 to 80, 80 to 100, 101 to 150, 151 to 200, 201 to 250, 251 to 300, 301 to 350, 351 to 400, 401 to 500, 501 to 600, 601 to 800, 801 to 1000, 1001 to 2000, 20001 to 3000, >3000	ADD value ranges: 1 to 10, 11 to 20, 21 to 30, 31 to 40, 41 to 50, 51 to 60, 61 to 70, 71 to 80, 81 to 90, 91 to 100, 101 to 110, 111 to 120, 121 to 140, 141 to 160, 161 to 180, 181 to 200, 201 to 250, 251 to 300, 301 to 350, 401 to 500, 501 to 600, 601 to 800, 801 to 1000, >1000.
Decomposition Stage	Qualitative stage of decomposition	Discrete	Chance	0.13	0.11	Early, Moderate, Advanced, Skeletonization.	
Death Location	Place of death	Discrete	Chance	0.16	0.25	Indoors, Outdoors.	Indoors, Outdoors, Vehicle
Manner of Death	Determination of how the death occurred	Discrete	Chance	0.58	0.44	Accidental, Homicide, Suicide, Natural, Undetermined.	
Cause of Death	Determination of why the death occurred	Discrete	Chance	0.36	0.79	Asphyxiation, Trauma, Drugs and/or poisoning, Natural, Undetermined	
Body Position	In-situ position	Discrete	Chance	0.24	0.46	Kneeling, Lateral, Prone, Supine, Seated, Suspended.	
Season	Meteorological	Discrete	Chance	0.00	0.71	*Excluded due to sensitivity analysis of 0.00*	Spring, Summer, Autumn, Winter
Temperature	Recorded at the scene (°C)	Interval	Chance	0.00	0.37	*Excluded due to sensitivity analysis of 0.00*	-5 to 0°C, 1 to 5°C, 6 to 10°C, 11 to 15°C, 16 to 20°C, 21 to 25°C, 26 to 30°C, 31 to 35°C
BMI	Body Mass Index	Discrete	Chance	0.00	0.24	*Excluded due to sensitivity analysis of 0.00*	Underweight, Normal, Overweight, Class I Obesity, Class II Obesity, Class III Obesity.

Table 3 Bayesian Belief Network Parameters for the UK (n=78) and US (n=250) models of PMI estimation

Model Validation

The BBNs of PMI estimation were validated independently by applying the taphonomic variables of additional 'blind PMI' validation cases in the UK (n=10) and the US (n=28) to the nodes in the respective BBNs. The frequencies of taphonomic variables represented in the validation cases are presented in Figure 6.

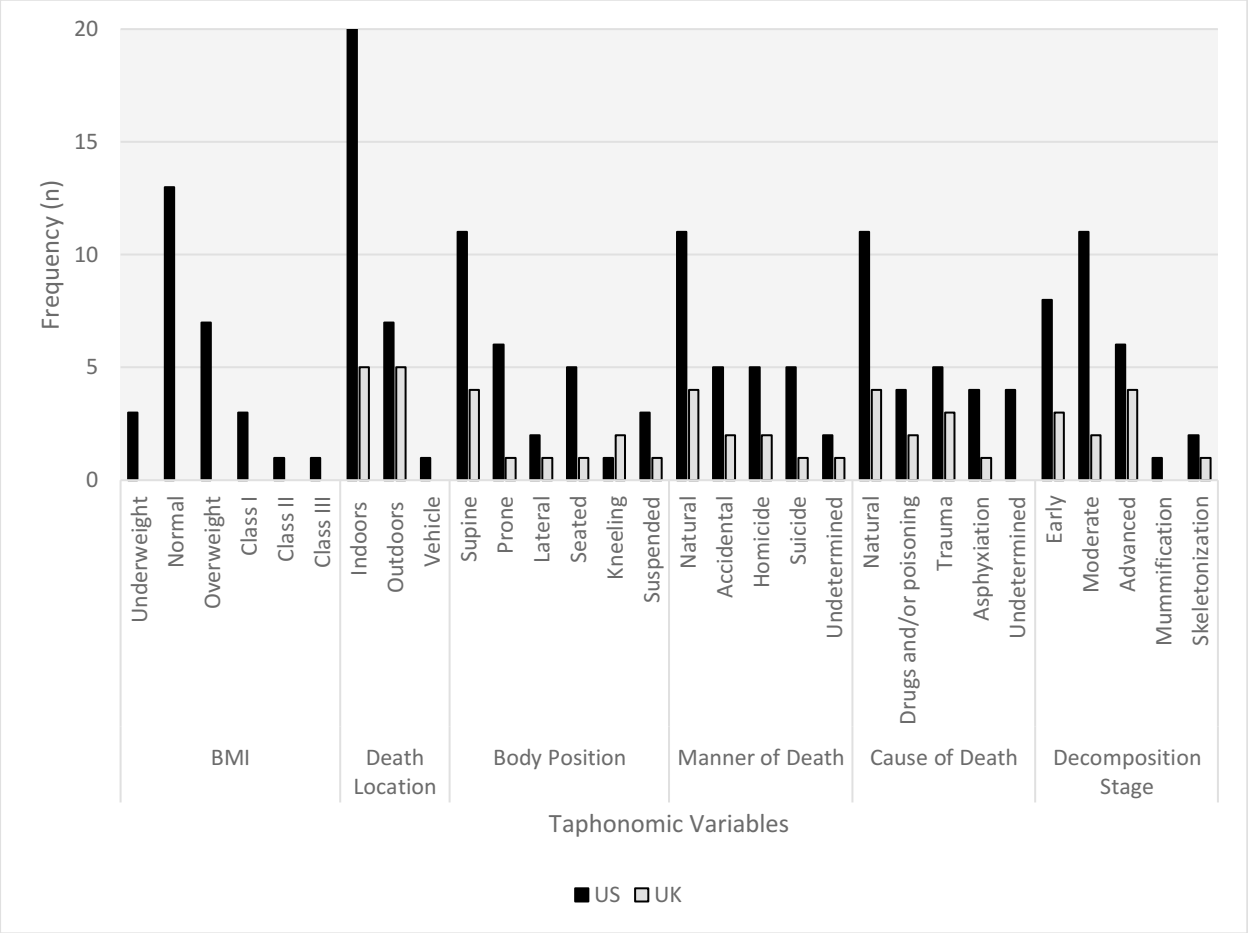

Figure 6. Frequency of taphonomic variables in validation cases for the US (n=28) and the UK (n=10).

Importantly, all taphonomic variables were represented in the US validation data. Conversely, the UK had no cases of 'mummification' for validation, and the BMI was not recorded in the UK validation cases since the BMI node was excluded from the UK BBN. In the US validation cases, the TDS ranged from 5 to 18, whereas the UK cases conferred a shorter range from 6 to 15 TDS. Similarly, there was a wide range of ADD in both the US (1 to >1000) and the UK (11 to >3000).

The accuracy of the PMI estimations was assessed in the HEval node. The node HEval enables the value of evidence to be quantified, i.e., the value of the PMI estimation in relation to the prior last known alive (LKA) information. In the prior LKA node, the user inputs the last known alive data as either a specific day (e.g., 5 days) or interval (e.g., 22 to 25 days). The HEval node has two arbitrary states: state 0, which supports the prior LKA hypothesis (e.g., that the person was last seen less than or equal to 7 days), or state 1, which is the null hypothesis and in the previous example would calculate the posterior probability that the person was last seen alive more than 7 days. The HEval node is automatically calculated from the posterior probability distribution of the PMI estimation node, which is influenced by the input of all taphonomic variables via the TDS.

An example case model output from a US validation case is presented in Figure 7. In this case, there was a natural manner and cause of death. The body was found indoors in winter, lying laterally and in a moderate stage of decomposition (TDS 9). The body was exposed to the temperature range of 21-25°C and 301 to 500 ADD. The experimental hypothesis was based on the prior last known alive information, which stated that the individual was last sighted 2 weeks prior to discovery. The null hypothesis, therefore, stipulated that the resulting PMI was greater than 14 days (Figure 7).

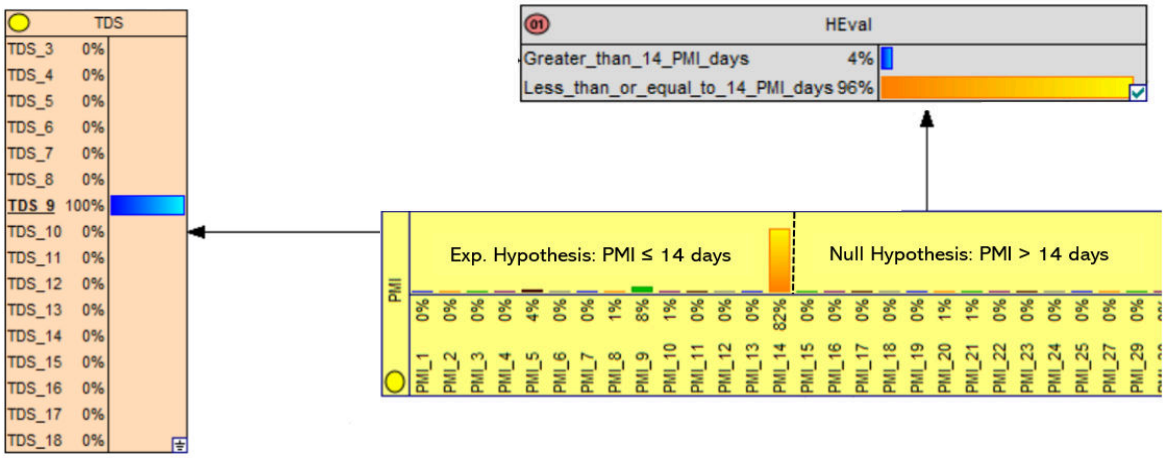

Figure 7 – Example of validation case showing posterior probability distribution in the US Model of PMI estimation. The bar chart in the 'PMI' shows the posterior probability distribution of the possible PMI based on the case details inputted in the chance nodes. This validation case had a TDS of 9. The HEval node indicates that the posterior probability of a PMI less than or equal to 14 days is 96%, whereas the probability of a PMI greater than 14 days is 4%. The actual PMI for this case was 14 days. The model estimates an 82% probability of the PMI being 14 days.

The US BBN outperformed the UK BBN in terms of support for the experimental hypothesis and accuracy of the PMI prediction. In the US, 75% of validation cases had a PMI accuracy between 73 to 100% (n=21), whereas the remaining 25% of cases conferred a PMI accuracy of 39-62% (n=7) (Figure 8). Conversely, in the UK, 40% of validation cases had a PMI accuracy between 88 to 100% (n=4), and the remaining 60% of cases had a PMI accuracy between 35 to 47% (n=6) (Figure 9). On average, the US model estimated a posterior probability of 86% that the PMI on, or less than, the actual PMI (SD ± 15.6, n=28) (Figure 8), compared to 81% in the UK (SD ± 18.2, n=10) (Figure 9). Furthermore, the mean accuracy of the PMI estimation was significantly higher in the US at 78% (SD ± 17.8, n=28) compared to the UK at 58% (SD ± 30.2) ($p<0.05$, n=38). However, the range of posterior probabilities for the correct PMI was broader in the US (48 to 100%) than in the UK (55 to 100%). There was an overall wide variety in PMI accuracy for both the US (39 – 100%, Figure 8) and the UK (25 – 100%, Figure 9).

The actual PMI appeared non-influential to the accuracy of the PMI estimation in both the US and the UK BBNs, meaning that the length of time the person had been deceased had no bearing on whether the PMI estimation was correct. This was evidenced by the lower posterior probabilities of PMI accuracy assigned to some cases at shorter time intervals of 2 (63%), 4 (48%), and 5 days (57%), a mid-range PMI of 16 days (48%) and the longest PMI of 99 days (65%), where the percentage in brackets represents the posterior probability of the PMI being on, or less than, the actual PMI day (Figure 8). Conversely, in the UK, the probabilities of the experimental hypothesis being correct were lower on PMI days 7 (55%), 35 (51%), and 54 (58%) (Figure 9).

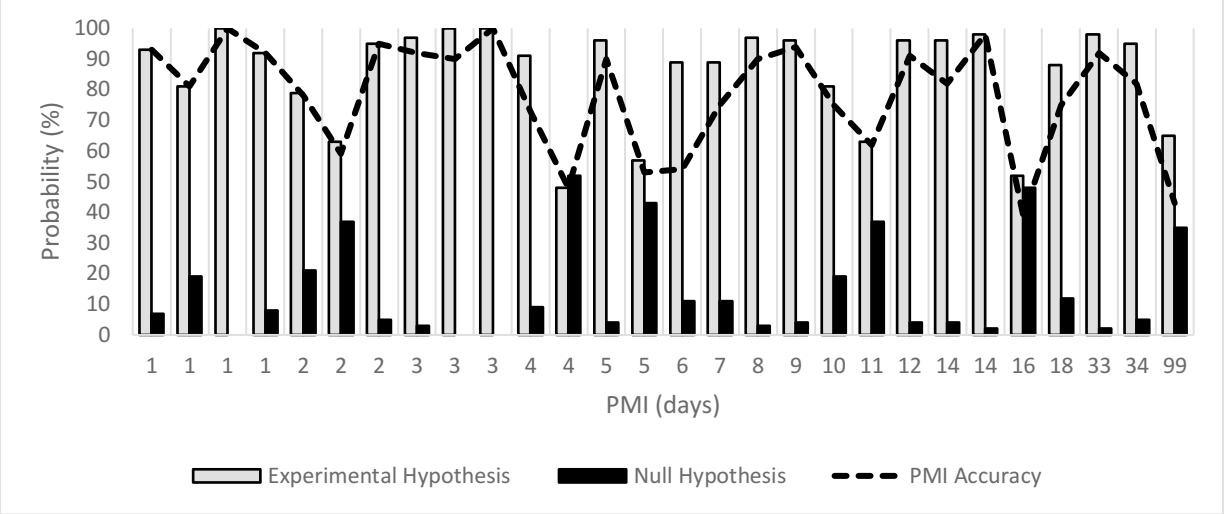

Figure 8 US validation cases probability of PMI estimation (n=28). The experimental hypothesis is depicted in the 'HEval' node and is the probability state that the PMI is less than or equal to x number of days determined by the prior LKA node. The null hypothesis is also depicted in the 'HEval' node and is the probability state that the PMI is more than x number of days (prior LKA node). The accuracy of the PMI estimation is represented by the dotted black line and measures how accurately the US model estimated the exact PMI of the validation case being tested.

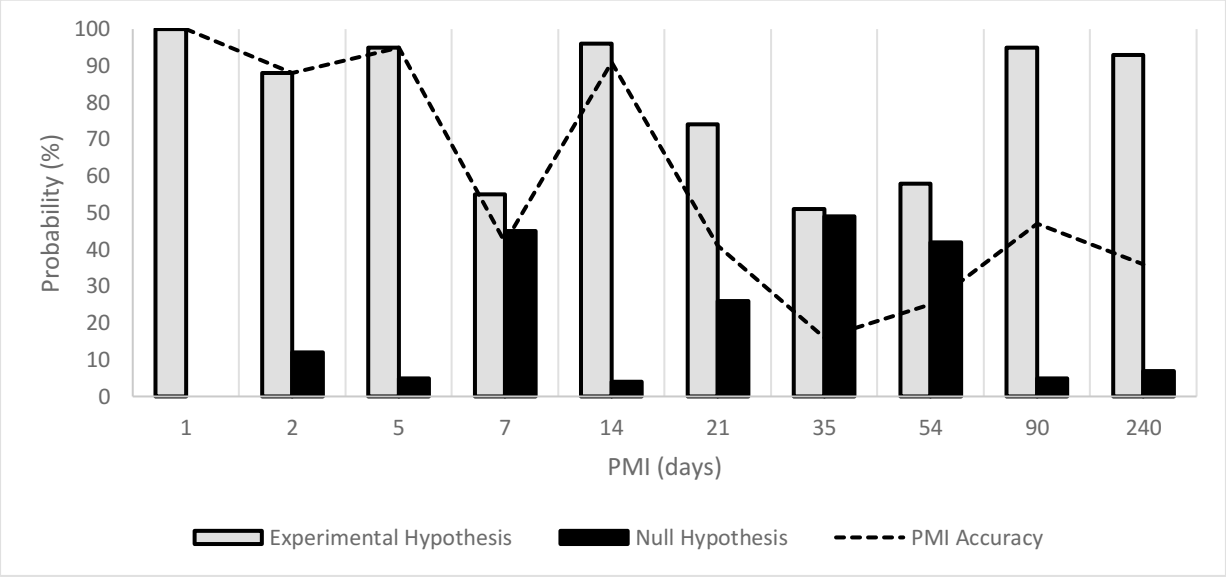

Figure 9 UK validation cases probability of PMI estimation (n=10). The experimental hypothesis is depicted in the 'HEval' node and is the probability state that the PMI is less than or equal to x number of days determined by the prior LKA node. The null hypothesis is also depicted in the 'HEval' node and is the probability state that the PMI is more than x number of days (prior LKA node). The accuracy of the PMI estimation is represented by the dotted black line and is a measure of how accurately the US model estimated the exact PMI of the validation case being tested.

PMI Accuracy and Taphonomic Variables

High PMI accuracy was assigned to cases where the actual PMI was predicted within ≥70% probability. Low PMI accuracy cases, therefore, ranged between 0 to 69% probability of the estimated PMI being correct. In the US, 7 cases conferred low PMI accuracy (39 to 62%), whereas, in the UK, low PMI accuracy ranged from 35 to 47% (n=6). Low PMI accuracy cases from both the US (Figure 10) and the

UK (Figure 11) were compared to high PMI accuracy to determine any patterns in the taphonomic variables that influenced the PMI accuracy rate.

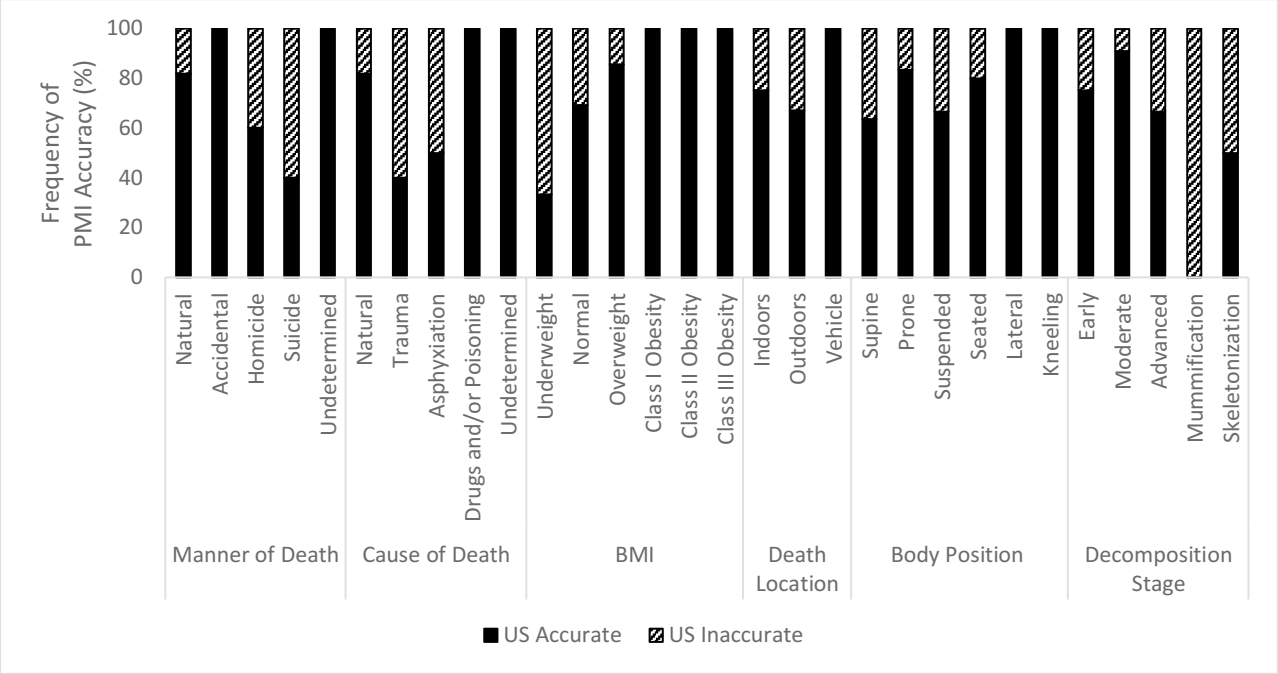

Figure 10 Frequency percentage of PMI Accuracy distributed by Taphonomic Variables in US validation cases (n=28).

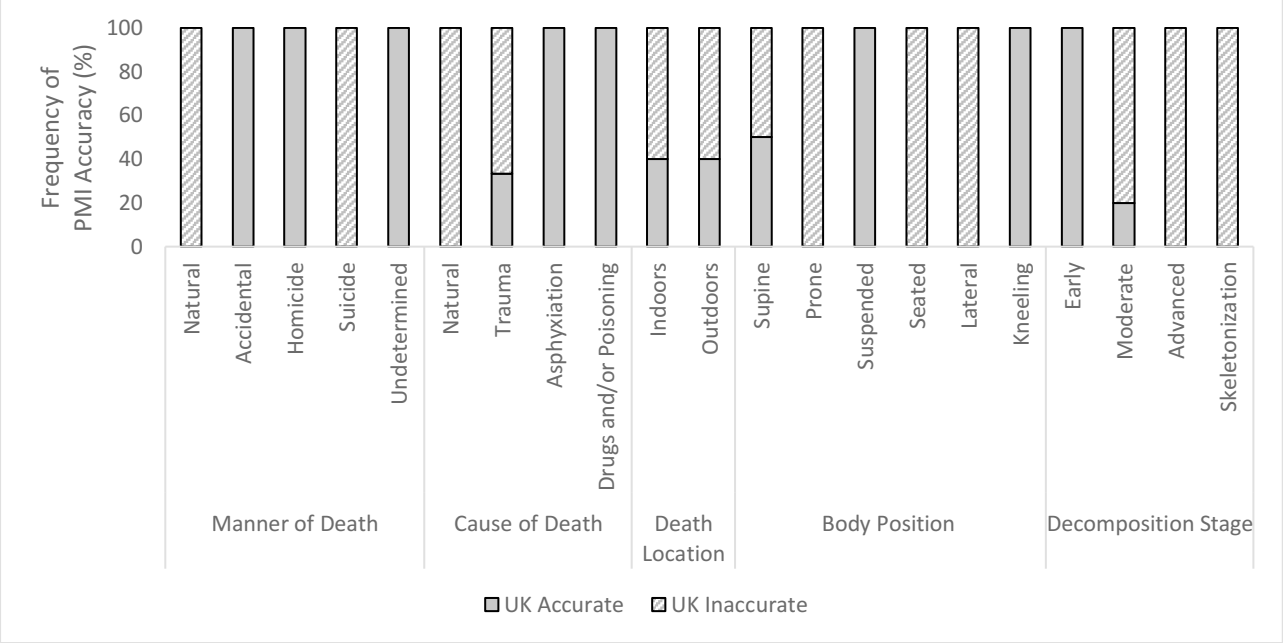

Figure 11 Frequency percentage of PMI Accuracy distributed by Taphonomic Variables in UK validation cases (n=10).

In the US and the UK, all accidental and undetermined deaths accurately predicted the PMI (meaning the estimated PMI conferred an accuracy of ≥70%) (Figures 10 and 11). However, in the UK, homicide cases also accurately predicted the PMI. Natural causes of death were more accurately predicted in the US than in the UK, with 80% conferring accurate predictions in the US (n=11), whereas all UK natural deaths were inaccurately predicted (n=4).

Drugs and/or poisoning cases exclusively conferred accurate PMI predictions in the US (n=6) and the UK (n=2). Conversely, US undetermined deaths (n-2) and the UK asphyxiation case also conferred accurate PMI predictions. The trauma cause of death consisted of accurate and inaccurate PMI predictions in both the US and the UK.

The US conferred a higher percentage of PMI accurate cases in indoor and outdoor deaths than the UK, and vehicles were exclusively PMI accurate in the US (Figure 10). The body positions consisted of both accurate and inaccurate PMI cases, with kneeling cases producing exclusively accurate PMI estimations in both the US (n=1) and the UK (n=2).

Early decomposition represented exclusively accurate PMI predictions in the UK (n=3) and conferred a higher proportion of accurate PMI predictions in the US (75%, n=6). This coincides with low TDS of 6 and 7 being only present in accurate PMI cases for both countries. Advanced decomposition and skeletonization UK cases (n=2) were exclusively inaccurate at predicting the PMI. In contrast, 50% of US skeletonization cases were inaccurately predicted (n=1), and one mummification case was also inaccurately predicted in the US (Figure 10). In both countries, higher TDS of 12 to 18 were more frequent in the inaccurate PMI cases (results not shown).

Temperature appeared non-influential to the accuracy of the PMI predictions in US cases. While 21 to 25°C was the most common range in inaccurate cases (n=6), this temperature range was also present in accurate cases (n=14) (results not shown). In the UK, shorter ADD ranges produced more accurate PMI estimations (11 to 20, 21 to 30, and 61 to 80), except for 251 to 300 ADD, which was also accurate. Longer ranges (301 to 1000 ADD) were exclusively inaccurate (n=6). Similarly, in the US, ADD ranges up to 40 ADD exclusively conferred PMI accuracy (n=5), and longer ADD ranges (<1000) were inaccurate (n=1); however, mid-range ADDs (between 41 to 1000 ADD) were both accurate and inaccurate (n=23).

Value of Evidence

The value of evidence and associated qualitative scale of conclusions of the validation cases PMI prediction accuracy is presented in Table 4. Notably, neither the US nor the UK dataset represented any cases below ‘moderate’ support for the BBN-derived PMI probability. The US had a higher proportion of 'moderate-strong' confidence in the validation PMI cases (64%, n=18) compared to the UK (50%, n=5). This was supported by the mean value of evidence being slightly higher for the US (431) than the UK for the UK (409); however, both values correlated with 'moderate-strong' PMI support, and a t-test revealed no significant differences between the value of evidence values between the countries ($p<0.05$, n=38). The US had fewer 'moderate' PMI support cases (29%, n=8) compared to the UK (40%, n=4); however, the US had a lower proportion of strong support cases (7%, n=2) than the UK (10%, n=1).

Interestingly, the actual PMI of the validation cases appeared uninfluential to the value of the PMI estimation. This became apparent when short PMIs such as 1 to 7 days had both moderate and moderate-strong cases in the validation datasets (Table 4). Similarly, the 'moderate-strong' confidence was widespread among short and long PMIs.

	US			UK		
Case	PMI (days)	Value of Evidence	Interpretation	PMI (days)	Value of Evidence	Interpretation
1	16	269.75	Moderate-Strong	35	24.98	Moderate
2	99	462.43	Moderate-Strong	54	67.67	Moderate
3	4	11.89	Moderate	240	318.86	Moderate-Strong
4	5	14.45	Moderate	21	44.59	Moderate
5	6	194.18	Moderate-Strong	7	11.00	Moderate
6	2	12.49	Moderate	90	456.00	Moderate-Strong
7	11	83.43	Moderate	2	359.33	Moderate-Strong

8	4	130.32	Moderate-Strong	14	456.00	Moderate-Strong
9	18	604.78	Moderate-Strong	5	456.00	Moderate-Strong
10	10	208.89	Moderate-Strong	1	1900.00	Strong
11	7	126.75	Moderate-Strong			
12	2	27.59	Moderate			
13	1	22.38	Moderate			
14	34	931.00	Moderate-Strong			
15	14	376.00	Moderate-Strong			
16	3	784.93	Moderate-Strong			
17	8	1045.44	Strong			
18	5	261.71	Moderate-Strong			
19	12	776.00	Moderate-Strong			
20	33	2401.00	Strong			
21	1	60.38	Moderate			
22	3	256.36	Moderate-Strong			
23	1	69.75	Moderate			
24	9	726.00	Moderate-Strong			
25	2	139.33	Moderate-Strong			
26	13	767.67	Moderate-Strong			
27	3	784.93	Moderate-Strong			
28	1	519.76	Moderate-Strong			
	Mean	431.02	Moderate-Strong	**Mean**	409.44	Moderate-Strong
	SD	493.58		**SD**	528.72	

Table 4 – Value of Evidence for US and UK validation cases of PMI estimation

Discussion

The main aim of this study was to develop and compare the accuracy of two environmentally different Bayesian Belief Networks (BBNs) for PMI estimations in UK and US medico-legal death investigations. Using decomposition data from two countries facilitated a rigorous comparison of the most dominant taphonomic variables affecting decomposition and ensured that these were factored into the resulting PMI estimations. This paper presents a novel PMI estimation model that can account for the combination of intrinsic, scene and environmental variables of decomposition that may uniquely present in a case. While it has been previously argued that a 'one size fits all' model is not fit for PMI estimation purposes [24,43], the advantage of the BBN eliminates this in its ability to base the PMI estimation on the set of presenting taphonomic variables that are inputted for each case. The BBNs are flexible in allowing the posterior probability distribution of the PMI to account for the prior last known alive information (inputted in the HEval node), even if it is presented as a range (e.g., 1 to 2 weeks). One logical solution is provided by applying coherent probabilistic reasoning to PMI estimations to model the complexities of human decomposition that can quantify the combined effect of several uncertainties surrounding the PMI estimation. This approach harbors several benefits, including communicating the PMI with an associated degree of confidence and providing predictive power on unknown PMI cases.

Both models conferred predictive power of the PMI with a mean posterior probability of 86% and 81%, in favor of the experimental hypothesis (that the PMI was on, or less than, the prior number of last known alive days) for the US and UK validation cases, respectively. In addition, neither the US nor the UK dataset represented any cases below 'moderate' support in terms of the value of PMI evidence. However, the US model outperformed the UK BBN in terms of the proportion of cases that supported the experimental hypothesis, the accuracy of the actual PMI predictions, and the qualitative interpretation of the value of PMI evidence. This could be due to the larger sample size of the US

training dataset, which presented a broader range of taphonomic variable combinations based on the PMI estimation of the validation cases. Larger sample sizes increase the precision of BBNs and are more representative of the overall population [36] and also harbour the potential to predict the PMI in cases where the last known alive data is unknown. Conversely, the UK model's PMI predictions were less accurate due to the fewer combinations of taphonomic variables embedded in the smaller sample UK training dataset.

Interestingly, the actual PMI appeared non-influential to both the accuracy and value of the PMI estimations. Validation cases that accurately predicted the PMI within a ≤70% probability and conferred a 'moderate-strong' value of PMI evidence were present across *both* short and long PMIs in the US and UK models. These findings support the capability of the BBNs to predict the PMI with confidence across widespread PMI ranges, contrary to the previous suggestion that PMI estimations confer greater inaccuracy at late PMIs [52]. The predictive power of the BBNs is based upon the quantity (and quality) of decomposition data inputted. When more cases are inputted into the training dataset (presenting many combinations of taphonomic variables at different PMIs), the BBN becomes more rigorous, harboring the potential to improve PMI predictions across all time intervals since death.

The stage of decomposition appeared to affect the accuracy of the BBN-derived PMI estimations for both the US and the UK, with early decomposition cases conferring more accurate PMI predictions than the later decay stages. This was also true for the control dataset, where the leptokurtic curve for a TDS of 6 (representing livor mortis, rigor mortis, and vibices) conferred the least variability in the known PMI with cases densely populated around the shorter mean PMI of 5 days. This could be due to: i) the complex interactions between taphonomic variables that precede as the PMI increases and ii) the accuracy of early decomposition markers to predict the PMI. The latter is also supported by a wealth of previous research that focuses on post-mortem biochemical markers (PBMs) and early physiological changes of decomposition (e.g., livor mortis, rigor mortis), which correlate to a PMI of ≤72 hours [13,18,53].

Temperature was excluded from the UK model due to its weak influence on the TDS. The UK dataset conferred the least variability in temperature ranges given its mild temperate climate, rendering the relationship between temperature and decomposition indistinguishable. In the US cases, scene temperature appeared non-influential to the accuracy of the PMI predictions, which is not dissimilar to previous findings [4,13]. However, the scene temperature readings may not have accurately reflected the actual temperature the bodies had been exposed to since death. Given the retrospective nature of the UK and US cases, it was not possible to record daily temperatures for the duration of the PMI, which provides scope for the use of ADD.

It has previously been proposed that the combination of the accumulated temperature over time encompassed in ADD is a more accurate predictor of the PMI [4]. The ADD threshold for PMI accuracy was greater for the UK than the US, with no inaccurate PMI cases below 80 ADD and 40 ADD, respectively. This could be due to climatic differences between the two countries, where a combination of dry heat and high humidity in the continental climate of the Allegheny County in the US promotes decomposition (by delaying desiccation) at shorter ADDs. This is further supported by our finding that higher TDS scores of 12 and 15 (reflecting advanced decomposition) were reached at lower mean ADDs in the US compared to the UK.

In the US, season, temperature, and BMI were included in the BBN but excluded in the UK model due to their weak relationship with TDS. This further supports speculation that taphonomic variables' effect on decomposition differs between geographic regions [24]. However, it cannot be excluded that the smaller UK training dataset restricted the sensitivity analysis of important relationships among taphonomic variables, which may explain why more variables were removed from the UK BBN. The derivates of sensitivity analysis are specific to the unique set of observations encompassed in the BBN.

If additional test cases were added to the model, the derivatives would be automatically recalculated and may produce an entirely different set of sensitivity results [49].

In the US, season and temperature appeared to have a limited effect on the accuracy of PMI cases (results not shown); however, other variables such as BMI did appear to influence the PMI accuracy. Underweight cases were largely inaccurate, whereas class I to III obesity cases conferred accurate PMI predictions. Studies have reported conflicting findings regarding the variability of body mass on the progression of decomposition [43,55]. A low BMI may be associated with early-onset mummification since thinner individuals tend to desiccate quickly [10]; however, the leathery appearance of skin in the TDS system is assigned a high decomposition score which did not correlate to the shorter PMI of the 'underweight' cases. In cases of advanced decomposition associated with longer PMIs where soft-tissue loss has occurred, the BMI recorded at post-mortem is not a true reflection of the BMI at the time of death. It is recommended that future experimental taphonomy studies could quantify soft-tissue loss in control cases (from PMI day 1 onwards), to further examine the relationship between BMI, decomposition stage, and the subsequent effect on PMI estimation.

The BMI was calculated at the post-mortem. This detail has been added into Table 1. We agree that soft tissue loss could cause an inaccurate reflection of actual BMI at the time of death. However, this study used retrospective cases from a medico-legal death investigators office, meaning the BMI at the time of death was not possible to record (unless the body had a PMI of 1 day, in which case the BMI would be more accurate). We have added this in as a limitation to the discussion and incorporated your suggestion of estimating mass loss in a control sample (where it can be measured from PMI day 1 onwards) for a future study.

Of the taphonomic variables that were comparable between the BBNs, there were notable differences in their effect on the PMI accuracy. For example, US natural deaths conferred accurate PMI predictions, whereas UK natural deaths were inaccurate. This could be explained by the lower predictive power of the UK BBN. However, it cannot be excluded that the natural cause of death, combined with other taphonomic variables, could have accounted for these differences. Additional validation cases would be needed to explore this further. UK homicide cases conferred only accurate PMI predictions, which is important since this is when the PMI becomes critical to the police investigation.

Conversely, the US homicide cases had both inaccurate and accurate PMI predictions. This could be due to the association of the homicide manner of death with trauma, where gunshot wounds were more common in the US than in the UK and can alter the trajectory of decomposition [54]. Accidental and undetermined manner of deaths, along with drugs and/or poisoning cause of death, conferred only accurate PMI predictions in both the UK and US. These cases were associated with the early decomposition stage, which was a more accurate predictor of the PMI and may explain these findings.

There were also similarities in the influence of taphonomic variables on TDS between the UK and the US. Indoor cases conferred more accurate PMI predictions than outdoor cases in both models. Decomposition trajectories differ between indoor and outdoor environments in terms of greater insect access outdoors, temperature stability indoors, and the fluctuation of environmental variables outside, which may collectively be held accountable for this [4,7,12]. It is also possible that other environmental variables such as wind, rain, and humidity, which were not recorded in this study, could have further contributed to this effect. It also cannot be excluded that the greater frequency of indoor cases in both BBNs could be held accountable for the higher predictive power of indoor PMI estimations. Since both UK and US training cases represented fewer cases of outdoor decomposition, it is recommended that future studies incorporate a greater proportion of outdoor cases to increase confidence in the PMI predictions. Furthermore, with a greater outdoor sample size, it would then be possible to introduce further sub-categories detailing the outdoor death location (e.g., buried, woodland, railway tracks), provided validation cases also represented these aforementioned variables to test PMI prediction accuracy.

The UK had the slowest rate of decay, with the highest TDS of 18 occurring at a mean of 470 PMI days (7815 ADD), compared to 131 PMI days (2877 ADD) in the US and 76 PMI days (1634 ADD) in the control. The variability in decomposition and ADD justified the creation of two environmentally different BBNs. Many contributing taphonomic variables could explain these differences; however, it is most likely that ADD was a significant accelerating factor of TDS, given the proportionate linear increase to the mean PMI.

The daily TDS observations of the control dataset facilitated an understanding of the occurrence, duration, and stage of the decomposition accumulation in relation to the PMI and ADD. The probability distribution function of the control decomposition data revealed PMI and ADD uncertainty with TDS progression, meaning that low TDS (e.g., 6 to 9) was correlated more closely with short PMIs and ADDs. In contrast, higher TDS (e.g., 12 to 15) were assigned at much broader PMIs and ADDs. The original researchers of the TDS model aired caution on inaccurate PMI estimations when cases presented a combination of low TDS at longer PMIs [5]. The time-lapse in longer PMIs inevitably provides more opportunities for the complex inter-relationships of taphonomic variables to affect the decomposition trajectory and confidence in the PMI correlation. However, these observations support the development of BBNs, since they allow for the input of many taphonomic variables that may be apparent in such cases to inform the PMI estimation.

The taphonomic variables in this study reflect a US and UK environment. The BBN approach is amenable to accommodating geographically dependent variables and is arguably one step further toward the creation of regional-specific PMI prediction models. It is notable that, as with all taphonomic variables examined in this study, their effect on decomposition was examined in totality. Recording individual decomposition characteristics has previously been recommended to escape the dominance of stage-specific criteria in decomposition scoring models [13]. A recommended future approach may be to incorporate individual decomposition characteristics into the BBN to assess the effect of taphonomic variables on subsequent PMI estimations. Furthermore, it is encouraged that additional training datasets are created for sub-sets of variables (e.g., entomology cases associated with soft-tissue loss) which could improve PMI predictability.

Conclusion

Decomposition processes are dependent on a considerable array of taphonomic variables that may affect subsequent PMI estimations. This is the first study to directly compare two different environmental-based models of PMI estimation capable of quantifying the uncertainty surrounding PMI estimations by introducing probabilistic reasoning and the unique combination of intrinsic, scene, and environmental variables that alter decomposition trajectory. Statistical modeling of the PMI estimation using Bayesian Belief Networks harbors the potential to include all decomposition cases previously excluded from other studies (e.g., children, drowning cases), provided that they are inputted in high frequency into the training dataset and additional blind cases are used to validate the model. The US model outperformed the UK model in terms of PMI accuracy; however, the UK model may benefit from additional validation cases to help improve our confidence in probabilistic PMI estimations.

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Solving the inverse problem of post-mortem interval estimation using Bayesian Belief Networks

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