Analyse de la relation entre la fréquence cardiaque et la température corporelle chez les enfants en état critique par apprentissage automatique

par

Émilie LU

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CETTE THÈSE A ÉTÉ ÉVALUÉE

PAR UN JURY COMPOSÉ DE:

Mme. Rita Noumeir, directrice de mémoire
Département de génie électrique, École de technologie supérieure

M. Philippe Jouvet, codirecteur
Unité des soins intensifs pédiatriques, CHU Sainte-Justine

Mme. Rachel Bouserhal, présidente du jury
Département de génie électrique, École de technologie supérieure

M. Jean-Marc Lina, membre du jury
Département de génie électrique, École de technologie supérieure

ELLE A FAIT L'OBJET D'UNE SOUTENANCE DEVANT JURY ET PUBLIC

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Analyse de la relation entre la fréquence cardiaque et la température corporelle chez les enfants en état critique par apprentissage automatique

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RÉSUMÉ

Le principal objectif de ce projet est d'explorer la relation entre la fréquence cardiaque (FC) et la température corporelle (TC) spécifiquement chez les enfants âgés de 0 à 18 ans admis à l'unité de soins intensifs pédiatriques (USIP). Pour atteindre cet objectif, nous avons utilisé des algorithmes d'apprentissage automatique (ML) pour explorer la relation complexe entre les deux signes vitaux, en allant au-delà des méthodes de régression linéaire traditionnelles pour une compréhension plus approfondie

Les résultats obtenus montrent une tendance cohérente de diminution de la FC avec l'augmentation de l'âge du patient, confirmant la corrélation inverse observée. Initialement, nous avons utilisé des modèles de régression linéaire conventionnels, et leurs performances étaient assez faibles. Plus précisément, nous avons observé une valeur de R-carré (R2) variant de 0,2967 à 0,3220, ainsi qu'une erreur quadratique moyenne (MSE) allant de 610,0736 à 620,5992. Ensuite, une analyse détaillée a identifié le modèle de Machines boosting de gradient (GBM) mis en œuvre avec une Régression quantile (QR) comme étant le modèle ayant la meilleure performance par rapport aux autres modèles. En utilisant la perte totale en quantile comme métrique d'évaluation pour les modèles QR, le modèle le plus performant GBM a démontré la plus basse perte totale en quantiles de 6,5069 ± 5,2507e-05. Il est important de mentionner que ce modèle, caractérisé par son noyau non linéaire, capture efficacement la relation non linéaire entre la FC, la TC et l'âge chez les jeunes patients en situation critique. De plus, nous avons conçu une interface utilisateur spécifiquement pour générer les prédictions de FC basées sur trois paramètres essentiels : la FC actuelle, la TC actuelle, et l'âge du patient. L'interface fournit en sortie les FCs prédites à différents percentiles ainsi que la position actuelle de la FC, permettant aux soignants de déterminer si la FC se situe dans la plage normale (entre le 5e et le 95e percentiles) ou non.

En résumé, cette recherche contribue à améliorer notre compréhension de la tendance entre la FC, la TC et l'âge chez les enfants gravement malades et remet en question les hypothèses établies sur la relation linéaire entre la FC et la TC. Le modèle ML, QR réalisé avec GBM, démontre son efficacité à capturer la dynamique non linéaire de ces paramètres physiologiques, soulignant l'importance de reconsidérer les hypothèses traditionnelles dans les contextes cliniques. De plus, nous espérons que l'interface utilisateur développée pour la prédiction de la FC pourra aider les cliniciens dans la prise de décisions cliniques.

Mots-clés: Apprentissage automatique, Apprentissage profond, Fréquence cardiaque, Température corporelle, Régression quantile, Unité des soins intensifs pédiatriques, Patients gravement malades

A Machine Learning-Based Study on Heart Rate and Body Temperature Relationship in Critical Ill Children

Émilie LU

ABSTRACT

The main objective of this project is to explore the relationship between heart rate (HR) and body temperature (BT) specifically in critical ill children aged 0 to 18 years admitted to the Pediatric Intensive Care Unit (PICU). To achieve this goal, we employed Machine learning (ML) algorithms to investigate the complex relationship between these vital signs, going beyond traditional linear regression methods for a more in-depth understanding of the association.

The results reveal a consistent trend of decreasing HR with increasing patient age, confirming the observed inverse correlation. Initially, we employed conventional linear regression models, and their performance was notably low. Specifically, we observed an R-squared (R2) value ranging from 0.2967 to 0.3220, along with a Mean squared error (MSE) ranging from 610.0736 to 620.5992. Furthermore, a detailed analysis identifies Gradient Boosting Machines (GBM) implemented with Quantile regression (QR), as the best model performance compared to others. Utilizing total quantile loss as an evaluation metric for QR models, the top-performing model demonstrated the lowest total quantile loss of 6.5069 ± 5.2507e-05. This model distinguished by its non-linear kernel, effectively capture the intricate non-linear relationships between HR, BT, and age in critically ill young patients at different quantiles. Moreover, we've designed a simple user interface specifically for generating HR predictions based on three essential parameters : current HR, current BT, and patient's age. The interface provides the predicted HR at various percentiles along with the current HR position, allowing caregivers to determine whether the HR falls within the normal range (between the 5th and 95th percentiles) or not.

In summary, this research contributes to enhancing our understanding of HR trends related to BT and age in critically ill children, challenging established assumptions about the linear relationship between HR and BT. The selected ML model, QR performed with GBM, demonstrate their effectiveness in capturing the non-linear dynamics of these physiological parameters, emphasizing the importance of reconsidering traditional assumptions in clinical contexts. Additionally, we aspire that the user interface developed for HR prediction can aid clinicians in making clinical decisions.

Keywords: Machine learning, Deep learning, Heart rate, Body temperature, Quantile regression, Pediatric Intensive Care Unit, Critical ill patients

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LISTE DES ABRÉVIATIONS, SIGLES ET ACRONYMES

CAPD	Cornell assessment of pediatric delirium
CDSS	Clinical decision support system
CHUSJ	Centre Hospitalier Universitaire Sainte-Justine
Comfort B	Comfort Behavior
DL	Deep learning
ECG	Electrocardiogram
ECMO	Extracorporeal membrane oxygenation
ETS	École de Technologie Supérieure
FLACC	Face, Legs, Activity, Cry, Consolability
FC	Fréquence cardiaque
GBM	Gradient boosting machine
LSTM	Long short-term memory
ML	Machine learning
MLP	Multilayer perceptron
MSE	Mean square error
NRS	Numerical Rating Scale
OLS	Ordinary least squares
PICU	Pediatric Intensive Care Unit
PPG	Photoplethysmograph
QR	Quantile regression
QL	Quantile loss
R2	R-squared
RASS	Richmond Agitation-Sedation Scale
RF	Random forest
RNN	Recurrent neural network

r-FLACC	revised Face, Legs, Activity, Cry, Consolability
SADC	Système d'Aide à la Décision Clinique
TC	Température corporelle
USIP	Unité de Soins Intensifs Pédiatriques

LISTE DES SYMBOLES ET UNITÉS DE MESURE

bpm	Battements par minute
°C	Degré Celsius
$\tilde{Y}$	Moyenne des valeurs de Y
τ	Niveau de quantile
n	Nombre d'observations
$\hat{Y}_i$	Valeur prédite
Y_i or y	Valeur réelle

INTRODUCTION

L’unité de soins intensifs pédiatriques (USIP) est un environnement spécialisé pour les enfants malades, où les changements physiologiques subtils peuvent servir de signes d’alerte sur leur santé. Les patients pédiatriques présentent diverses conditions médicales et groupes d’âge, entraînant des réponses physiologiques distinctes, en particulier lors des traitements médicamenteux et des interventions thérapeutiques. Ces cas complexes nécessitent une gamme d’interventions, une surveillance avancée et des soins intensifs. Étant donné la vulnérabilité des patients pédiatriques et la gravité de leur maladie, les avancées dans la compréhension et l’utilisation d’indicateurs physiologiques tels que la fréquence cardiaque (FC) et la température corporelle (TC) pourraient considérablement améliorer les soins prodigués par les cliniciens. En fournissant aux soignants des informations en temps réel sur l’état de la FC d’un patient, les cliniciens peuvent rapidement détecter de légères variations par rapport aux signes vitaux normaux, ce qui permet des interventions précoces pour améliorer l’état du patient. Cela permet également aux soignants de déterminer si la FC anormale est liée à la TC ou non. De telles informations peuvent aider les cliniciens dans leur processus de prise de décision clinique, en leur permettant de distinguer entre des fluctuations normales et des tendances préoccupantes, facilitant ainsi des interventions plus ciblées et réduisant au minimum les procédures médicales inutiles. Ainsi, cette approche permet également de contribuer à améliorer les protocoles cliniques, ce qui se traduit par une meilleure utilisation des ressources et une rationalisation des flux de travail, entraînant en fin de compte une réduction des coûts de santé. Idéalement, cet outil sera intégré au Système d’Aide à la Décision Clinique (SADC) de l’USIP du CHU Sainte-Justine pour soutenir les cliniciens dans leurs décisions cliniques, dans le but d’améliorer la qualité des soins aux patients (CHUSJ, 2024).

Alors que nous plongeons dans la compréhension de la relation complexe entre la FC et la TC, il devient crucial d’explorer les mécanismes physiologiques qui régissent ces paramètres vitaux.

Tout d'abord, le cœur est un organe musculaire qui agit comme une pompe dynamique en propulsant le sang oxygéné vers le cerveau, divers tissus et organes vitaux. Il joue également un rôle essentiel dans l'apport de nutriments et l'élimination des déchets du corps. Le cycle cardiaque, qui comprend des phases de contraction (systole) où un volume de sang est injecté à chaque battement cardiaque, ainsi que des phases de relaxation (diastole), régule cette action de pompage rythmique. La FC, définie par le nombre de battements de cœur par minute, est cruciale pour la physiologie cardiovasculaire. La demande en oxygène fluctue en fonction de l'activité, avec l'intervention de divers mécanismes, dont principalement le système nerveux autonome. L'activité sympathique augmente la FC, tandis que l'activité parasympathique la ralentit. Malheureusement, un dysfonctionnement du système cardiovasculaire peut entraîner des conséquences néfastes, telles que la morbidité et la mortalité (Draghici & Taylor, 2016).

La TC est régulée par le processus de thermorégulation, contrôlé par l'hypothalamus dans le cerveau. La thermorégulation joue un rôle crucial dans le maintien de l'homéostasie humaine en assurant une TC normale en réponse aux changements de température externe ou aux fluctuations internes. Elle implique un équilibre entre la perte et la génération de chaleur, visant à maintenir la température interne optimale nécessaire aux processus physiologiques, notamment au bon fonctionnement des enzymes et à la réponse immunitaire. Plusieurs mécanismes entrent en jeu lorsqu'il y a une variation de la TC. Lorsque la TC augmente, le corps répond en dissipant la chaleur par la transpiration, en réduisant le taux métabolique et en dilatant les vaisseaux sanguins près de la surface de la peau pour libérer la chaleur. À l'inverse, lorsque la TC diminue, le corps initie des mécanismes pour générer de la chaleur. Cela comprend la vasoconstriction pour préserver la TC centrale, les frissons et une augmentation du taux métabolique. Ces efforts combinés permettent au corps de produire plus de chaleur, aidant à contrer la baisse de température et à maintenir un environnement interne stable (Osilla, Marsidi & Sharma, 2018).

Dans cette thèse, l'étude commence par une analyse approfondie des résultats de recherche existant entre ces deux signes vitaux. Ensuite, nous nous concentrerons sur la démonstration des techniques utilisées pour mesurer la FC et la TC à l'USIP. Nous intégrerons une discussion sur le tableau des valeurs normales de FC et de TC, ainsi que sur les motivations de cette étude. Ensuite, nous fournirons un aperçu détaillé des techniques d'apprentissage automatique utilisées pour modéliser la relation complexe. En avançant, nous présenterons l'article rédigé dans ce contexte, exposant nos résultats de recherche et les perspectives tirées de l'intersection des approches traditionnelles et de l'apprentissage automatique. Enfin, nous conclurons cette étude par un résumé, discuterons des avenues potentielles pour la recherche future et des implications pratiques de notre étude sur l'amélioration des soins aux patients à l'USIP.

CHAPITRE 1

REVUE DE LITTÉRATURE

1.1 Dynamique entre la FC et la TC

Comprendre l'association entre la FC et la TC peut jouer un rôle crucial dans la surveillance de la santé globale d'un enfant. Cela peut également aider à la détection précoce et à traiter rapidement tout problème de santé. À ce jour, il n'existe aucun modèle ou technique établi spécifiquement conçu pour déterminer si une certaine FC basée sur la TC se situe dans la plage normale ou non. Les professionnels de la santé utilisent des principes physiologiques pour évaluer l'interaction de ces deux signes vitaux. Notamment, une tendance observée est que lorsque la TC augmente, il y a une augmentation correspondante de la FC. Des études menées chez des enfants et des adultes hospitalisés ont quantifié ces changements, démontrant une association linéaire.

En commençant par les enfants hospitalisés en soins primaires et aux urgences, des recherches approfondies ont examiné la relation et les études montrent de manière cohérente que la TC est un facteur indépendant influençant la FC, avec une augmentation moyenne d'environ 10 battements par minute (bpm) par degré centigrade. Notamment, Daymont, Bonafide & Brady (2015) and Davies & Maconochie (2009) ont utilisé des méthodes statistiques distinctes dans leurs enquêtes, où Daymont *et al.* (2015) ont créé une courbe de percentile en utilisant la distribution de la puissance exponentielle de Box Cox, tandis que Davies & Maconochie (2009) ont utilisé une régression quantile avec Stata, incorporant une équation polynomiale mathématique impliquant la TC, l'âge et $l'ge^2$ (Daymont *et al.*, 2015; Davies & Maconochie, 2009).

Les travaux de Thompson *et al.* (2009) et Heal, Harvey, Brown, Rowland & Roland (2022) mettent en évidence l'influence spécifique à l'âge de la TC sur la FC respectivement chez les enfants atteints d'infections aiguës et les enfants admis aux urgences. L'augmentation observée de la FC pour chaque augmentation de 1°C de la TC variait de 9,9 à 14,1 bpm (Thompson *et al.*, 2009). Thompson *et al.* (2009) ont utilisé des courbes de centiles pour décrire la FC attendue à différentes plages de température dans différents groupes d'âge, tandis que Heal *et al.* (2022) ont utilisé un modèle de régression linéaire multiple, où la FC est la variable dépendante et la TC est la variable indépendante. Heal *et al.* (2022) ont également approfondi l'étude de la relation en introduisant un terme d'interaction entre l'âge et la variable indépendante, en utilisant Stata pour l'analyse. En revanche, chez les enfants de 0 à 16 ans consultant aux urgences, ils ont constaté qu'une augmentation de 1°C de la TC entraînait une augmentation de la FC allant de 8,7 à 13,7 bpm, avec une moyenne observée étant de 12,3 bpm (Heal *et al.*, 2022).

Pour les adultes admis au service des urgences, des études ont montré qu'une augmentation de 1°C de la TC entraînait une augmentation d'environ 7 bpm de la FC (Kirschen, Singer, Thode Jr & Singer, 2020). Kirschen *et al.* (2020) ont effectué une régression linéaire, obtenant une signification statistique avec $p<0{,}05$. Chez les patients aigus dans le service des urgences, les résultats de Jensen & Brabrand (2015) ont indiqué que ceux présentant une TC dépassant $37,2C$ présentaient des changements significatifs de la FC, avec une augmentation de 7,4 ± 0,9 bpm par degré (Jensen & Brabrand, 2015). Jensen & Brabrand (2015) ont utilisé des analyses de régression linéaire et à variables multiples pour calculer le changement de FC par degré Celsius.

Les observations chez les adultes gravement malades admis en unité de soins intensifs (USI) ont révélé une corrélation linéaire entre la TC et la FC dans la plage de température de 32.0° à 42.0°C (Broman, Vincent, Ronco, Hansson & Bell, 2021). Pour chaque augmentation de 1°C dans cette plage, la FC a montré une augmentation linéaire de 8.35 ± 0.50 bpm (Broman *et al.*, 2021). La régression linéaire multiple de Broman *et al.* (2021) comprenait la température, le sexe, l'âge, l'hémoglobine, le magnésium, l'excès de base, l'utilisation d'agents adrénergiques et le score SOFA comme covariables dans le modèle (Broman *et al.*, 2021).

1.2 Techniques de mesure de la FC et de la TC à l'USIP

Dans l'USIP, la FC et la TC sont mesurées de manière routinière à l'aide d'instruments médicaux standard. Dans cette section, nous fournirons une description détaillée des différentes techniques de mesure pour ces deux signes vitaux.

La surveillance de la FC peut être effectuée avec précision grâce à deux techniques différentes. La première technique, pour une surveillance continue en temps réel, implique l'utilisation d'électrodes placées de manière stratégique sur la poitrine du patient pour générer un électrocardiogramme (ECG), offrant une représentation continue et détaillée de l'activité électrique cardiaque du patient. Cette méthode assure que les professionels de la santé ont accès à des informations en temps réel sur le rythme cardiaque du patient et peuvent détecter toute anomalie éventuelle. Avec l'ECG, le processus de détermination de la FC implique la mesure des intervalles de temps en millisecondes entre les ondes R consécutives présentes dans les signaux électriques du cœur, tel qu'illustré dans la figure 1.1. Les ondes R apparaissent comme des pics marqués dans le signal ECG, indiquant le début d'un battement cardiaque et la dépolarisation des ventricules. En analysant précisément ces intervalles de temps, souvent appelés intervalles RR, les cliniciens et les algorithmes automatisés peuvent calculer la FC (Rahman *et al.*, 2021).

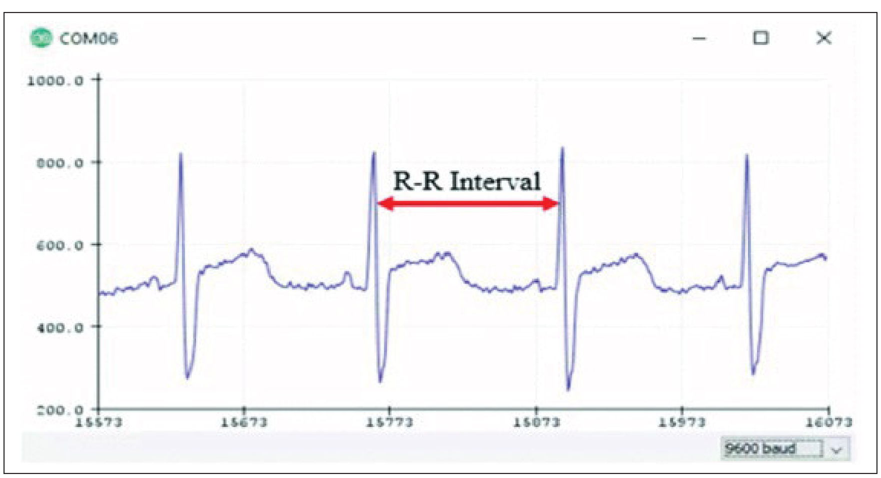

Figure 1.1 Fréquence cardiaque mesurée à partir des signaux ECG
Tiré de Rahman *et al.* (2021)

En alternative, le deuxième moyen de surveiller la FC est avec l'oxymètre de pouls, un dispositif non invasif attaché au doigt du patient. Dans la Figure 1.2, le dispositif fonctionne sur le principe de la spectrophotométrie d'absorption. Les photodétecteurs, ou photosenseurs, détectent les niveaux d'oxygène transportés (sang oxygéné = hémoglobine + oxygène = HbO2) ou non transportés (sang désoxygéné = hémoglobine = Hb) par l'hémoglobine dans les vaisseaux sanguins. Cette détection repose sur la lumière infrarouge (longueur d'onde de 800 à 940 nm absorbée par HbO2) et la lumière rouge (longueur d'onde de 600 à 700 nm absorbée par Hb) lorsqu'elle passe à travers le bout de doigt du patient. Une onde photopléthysmographique (PPG) est générée, où la FC est mesurée par l'intervalle de temps entre les pics successifs, représentant le volume sanguin maximal pendant un cycle cardiaque. Ce dispositif fournit non seulement des mesures précises de la FC, mais fournit également des données précieuses sur les niveaux de saturation en oxygène (Anzanpour *et al.*, 2020; Szakacs-Simon, Moraru & Perniu, 2012).

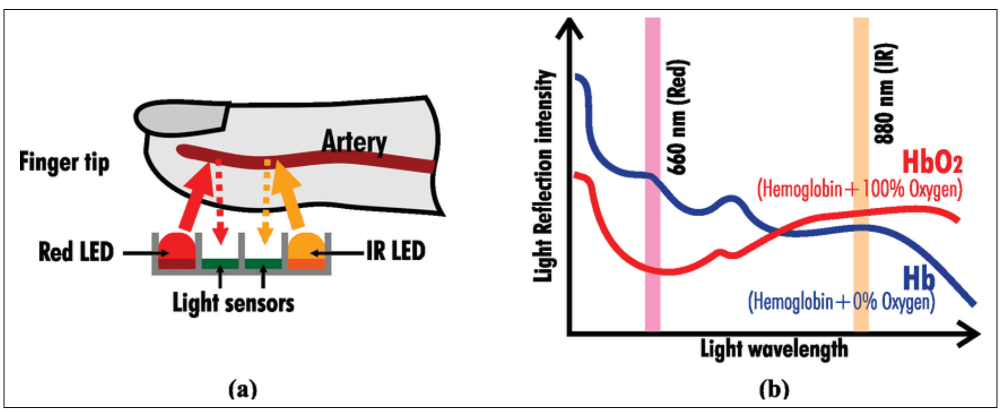

Figure 1.2 Principe de l'oximètre de pouls (a) Oximètre de pouls placé au doigt utilisant les lumières rouge et infrarouge pour mesurer la saturation en oxygène (b) Spectre d'aborsorption de l'hémoglobine oxygénée et déoxygénée en fonction de des lumière rouge et infrarouge
Tiré de Anzanpour *et al.* (2020)

La surveillance de la TC est un processus continu effectué à des intervalles de 30 secondes à l'aide de sondes ou de capteurs. Cette surveillance méticuleuse et fréquente est également complétée par des mesures manuelles prises toutes les 2 à 4 heures. Le choix de la méthode de mesure est crucial pour fournir une compréhension complète de la dynamique thermique du patient. Pour augmenter la précision de la mesure, la méthode choisie est adaptée à l'âge du patient. Plus précisément, pour les nouveau-nés jusqu'à 2 ans, la TC est mesurée soit par voie rectale soit par voie auriculaire. Dans le cas des enfants de 2 à 5 ans, les options de mesure de la température comprennent les méthodes rectale, auriculaire ou axillaire. Pour les enfants de plus de 5 ans, la TC peut être mesurée par voie buccale, rectale, auriculaire ou axillaire. Cette approche spécifique à l'âge garantit que les mesures de TC sont non seulement précises, mais également adaptées au confort de la méthode pour chaque groupe d'âge. Cette approche multiple de la surveillance de la TC assure une évaluation en temps réel et précise de la température centrale du patient, permettant aux soins de santé d'identifier et de traiter rapidement toute fluctuation ou anomalie (CHUSJ, 2020).

Enfin, l'intégration de diverses modalités de surveillance à l'USIP souligne l'engagement envers une approche globale et nuancée des soins aux patients. Cela garantit l'accès à des informations précises en temps réel pour orienter les décisions cliniques et les interventions.

1.3 Références des valeurs normales de la FC et de la TC pour les professionnels de la santé

En USIP, les professionnels de la santé s'appuient sur des tableaux et des références établis décrivant les valeurs normales de la FC et de la TC pour différents groupes d'âge. Ces références constituent des outils inestimables pour aider les cliniciens à identifier d'éventuelles anomalies ou déviations par rapport aux plages normales. En ce qui concerne la FC présentée dans la Figure 1.3, les valeurs de référence sont établies et adaptées à partir des normes de "Pediatric Advanced Life Support" (PALS) et sont déterminées en fonction de l'âge et de l'état du patient (UrgenceHSJ, 2011).

Âge	FC éveillé	FC endormi
Nouveau-né à 3 mois	85-205	80-160
3 mois à 2 ans	100-190	75-160
2 à 10 ans	60-140	60-90
>10 ans	60-100	50-90

Figure 1.3 Plage normale de la fréquence cardiaque regroupée par l'âge et l'état du patient
Tiré de UrgenceHSJ (2011)

Site utilisé	Variation normale de la température
Rectum	36,6 °C à 38,4 °C (97,9 °F à 101,12 °F)
Bouche	35,5 °C à 37,9 °C (95,9 °F à 100,22 °F)
Aisselle*	34,7 °C à 37,4 °C (94,5 °F à 99,3 °F)
Oreille*	35,8 °C à 38,0 °C (96,4 °F à 100,4 °F)

Figure 1.4 Plage normale de la température corporelle chez les enfants en fonction du site de mesure de la température
Tiré de CHUSJ (2020)

Quant à la TC présentée dans la Figure 1.4, les valeurs normales sont classées en fonction du site de mesure de la température. Il est essentiel que les professionnels de la santé tiennent compte de la plage de référence appropriée pour la méthode spécifique utilisée, garantissant une interprétation précise et une prise de décision clinique appropriée en fonction de l'âge et de l'état du patient CHUSJ (2020).

1.4 Motivation de l'étude

Comme mentionné précédemment, la FC et la TC sont des indicateurs critiques de la santé humaine. Plusieurs études portant sur des enfants et des adultes admis au service des urgences démontrent la relation linéaire entre ces deux signes vitaux. La capacité à surveiller et à évaluer précisément ces paramètres est essentielle pour prendre des décisions cliniques éclairées et fournir des soins optimaux aux patients.

La motivation de notre étude est ancrée dans la compréhension établie selon laquelle la FC co-varie avec la TC. L'exposition à des environnements froids peut entraîner une hypothermie et une diminution de la FC, tandis qu'une TC élevée causée par la fièvre, l'inflammation ou une infection entraîne souvent une augmentation de la FC. Surveiller ces variations est essentiel pour identifier d'éventuelles complications et fournir des interventions appropriées, car l'identification rapide de ces tendances peut guider des interventions médicales opportunes et efficaces.

Dans cette optique, l'objectif principal de cette étude est de fournir en temps réel aux professionnels de la santé une indication sur le positionnement de la FC par rapport à une plage normale, tenant compte à la fois de l'âge du patient et de sa TC. Cette information est cruciale pour anticiper d'éventuelles complications et prendre des mesures préventives ou thérapeutiques lorsque nécessaire. Plus spécifiquement, si la valeur de la FC est soit en dessous du 5e percentile, soit au-dessus du 95e percentile, elle est utilisée comme indicateur de la gravité de l'état d'un patient. Par conséquent, l'outil développé dans le cadre de ce projet sera éventuellement intégré au prototype de représentation visuelle de Yakob, Laliberté, Doyon-Poulin, Jouvet & Noumeir (2024) pour soutenir la prise de décision clinique en USIP du CHUSJ. En développant une compréhension plus claire de la relation entre la FC et la TC au sein de cette population avec une approche d'apprentissage automatique, cette étude dotera les soignants de la capacité à prédire plus précisément les interventions nécessaires. Elle améliorera la qualité globale des soins aux patients en USIP en facilitant des stratégies de traitement proactives et personnalisées pour chaque patient. Dans le futur, nous visons à établir si les mesures de la FC peuvent prédire les résultats des patients. De plus, nous étudierons si la normalisation de la FC peut améliorer la récupération des patients.

1.5 Apprentissage automatique

Durant les dernières années, l'intégration d'algorithmes d'apprentissage automatique s'est imposée comme un outil puissant dans la recherche en santé (Habehh & Gohel, 2021). Notre étude se concentre sur l'utilisation de techniques avancées, notamment des modèles de régression et des réseaux neuronaux. L'objectif ultime est non seulement d'identifier des motifs et des associations, mais également de développer un modèle prédictif robuste. Ce modèle vise à aider les professionnels de la santé à comprendre la variation de la FC en fonction de la TC. Grâce à l'intégration de méthodologies d'apprentissage automatique avancé, cette étude vise à faire progresser le domaine des soins intensifs pédiatriques, en fournissant aux cliniciens des informations utiles pour adapter les interventions et améliorer les soins globaux aux patients.

Dans notre étude, nous avons utilisé des modèles de régression réputés pour leur capacité à quantifier les relations entre les variables (Mahbobi & Tiemann, 2015). Ces modèles sont des outils précieux pour découvrir l'interaction complexe de ces paramètres physiologiques et pour révéler des relations prédictives potentielles. Initialement, nous avons utilisé des techniques de régression linéaire conventionnelles, car les études antérieures ont souligné la corrélation linéaire entre la FC et la TC chez les enfants et les adultes hospitalisés. Cela comprend la régression linéaire simple (Linear regression - LR), la régression linéaire multiple (Multiple linear regression - MLR), la régression polynomiale (Polynomial regression - PR) avec un degré de 1, les machines à vecteurs de support (Support vector machines = SVM), ainsi qu'un modèle statistique dérivé de l'étude de Davies & Maconochie (2009). Ces diverses formes de régression linéaire présentent chacune des avantages spécifiques et des contextes d'utilisation particuliers. Notamment, la régression linéaire simple est utilisée pour étudier la relation directe entre deux variables, tandis que la régression linéaire multiple permet de prendre en compte plusieurs variables simultanément. L'emploi de ces méthodes permet une analyse exhaustive et solide des données, facilitant la comparaison et l'évaluation des performances prédictives.

Pour une analyse plus approfondie, nous avons intégré la régression par quantile (Quantile regression - QR) dans l'étude. L'avantage de la QR réside dans sa capacité à effectuer à la fois des noyaux linéaires et non linéaires, où les modèles de régression non linéaires peuvent capturer des schémas plus complexes. Dans cette étude, la QR a été réalisée en utilisant des techniques d'apprentissage automatique conventionnelles avec un noyau linéaire, telles que les moindres carrés ordinaires (Ordinary least squares - OLS), et étendue à des noyaux non linéaires tels que les machines à gradient boosting (Gradient boosting machines - GBM) et les forêts aléatoires (Random forests - RF). Des modèles d'apprentissage profond (Deep learning - DL), comprenant des perceptrons multicouches (Multi-layer perceptrons - MLP), des réseaux neuronaux récurrents (Recurrent neural networks - RNN) et des réseaux neuronaux à mémoire à court et long terme (Long short-term memory networks - LSTM), ont également été utilisés en tant que noyaux non linéaires dans l'analyse QR. L'application de réseaux neuronaux, une sous-catégorie de l'apprentissage automatique caractérisée par sa capacité à reconnaître des motifs complexes dans les données. Les réseaux neuronaux, en particulier les architectures DL, excellent dans la capture de relations complexes et non linéaires qui peuvent échapper aux méthodes conventionnelles. En tirant parti des réseaux neuronaux, cette recherche aspire à améliorer la précision et la granularité de la compréhension des connexions dynamiques entre la FC et la TC chez les patients pédiatriques gravement malades.

Pour évaluer les performances de ces modèles, diverses mesures ont été prises en compte, telles que le coefficient de détermination (R-squared - R2) et l'erreur quadratique moyenne (Mean squared error - MSE) pour la régression linéaire conventionnelle, et la perte de quantile (Quantile loss - QL) pour la QR. Cette approche globale visait à fournir une compréhension robuste de la relation complexe entre la FC et la TC, en utilisant des techniques d'apprentissage automatique traditionnelles et avancées.

1.6 Lien vers l'article

Dans le chapitre suivant, nous présenterons l'article décrivant les résultats de notre étude sur la modélisation de l'association entre la FC et la TC chez les patients pédiatriques gravement malades âgés de 0 à 18 ans. En utilisant des techniques d'apprentissage automatique, notre étude vise à construire des modèles prédictifs qui permettent aux cliniciens de mieux comprendre et anticiper les dynamiques de la FC en fonction de la TC et de l'âge. Cette approche innovante offre aux professionnels de la santé des outils améliorés pour les soins aux patients, en exploitant l'analyse prédictive pour fournir des informations plus précises et opportunes sur l'interaction critique entre ces paramètres physiologiques.

En nous appuyant sur la revue de la littérature présentée précédemment, qui se concentre principalement sur la relation dynamique entre une variation de température et son effet sur la FC, nous avons observé un manque de modèles établis pour prédire la FC en fonction de l'âge et de la TC. De plus, les études précédentes ont principalement identifié une association linéaire entre la FC et la TC. En tenant compte de cela, nous avons initialement décidé d'employer des méthodes de régression linéaire traditionnelle pour modéliser la relation entre ces deux variables. L'utilisation de la régression linéaire nous a permis d'explorer l'association linéaire initiale observée dans les études précédentes. Il s'agissait d'une étape fondamentale dans notre recherche, fournissant une base pour notre analyse. Cependant, reconnaissant les limites des modèles linéaires dans la capture de schémas potentiellement complexes et non linéaires, nous nous sommes ensuite tournés vers d'autres méthodologies d'apprentissage automatique pour améliorer la précision et la flexibilité de nos modèles prédictifs.

Le lien entre notre revue de la littérature et l'article ultérieur réside dans l'évolution de notre approche. Alors que les méthodes de régression linéaire traditionnelles ont été initialement utilisées, l'incorporation de techniques avancées d'apprentissage automatique dans l'article représente une avancée pour fournir des observations plus nuancées dans la relation complexe chez les patients pédiatriques gravement malades.

CHAPITRE 2

HEART RATE AND BODY TEMPERATURE RELATIONSHIP IN CHILDREN ADMITTED TO PICU - A MACHINE LEARNING APPROACH

Emilie Lu[1] , Thanh-Dung Le[1] , Philippe Jouvet[2] , Rita Noumeir[1]

[1] Electrical Engineering Department, École de Technologie Supérieure,
1100 Notre-Dame Street West, Montreal, Quebec, Canada H3C 1K3
[2] CHU Sainte-Justine Research Center, CHU Sainte-Justine,
3175 Chemin de la Côte-Sainte-Catherine, Montreal, Quebec, Canada H3T 1C5

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2.1 Abstract

Vital signs have been essential clinical measures. Among these, body temperature (BT) and heart rate (HR) are particularly significant, and numerous studies explored their association in hospitalized adults and children. However, a lack of in-depth research persists in children admitted to the pediatric intensive care unit (PICU) despite their critical condition requiring particular attention. *Objective :* In this study, we explore the relationship between HR and BT in children from 0 to 18 years old admitted to the PICU of CHU Sainte-Justine (CHUSJ) Hospital. *Methods :* We applied Machine learning (ML) techniques to unravel subtle patterns and dependencies within our dataset to achieve this objective. Each algorithm undergoes meticulous hyperparameter tuning to optimize the model performance. *Results :* On a large database of 4006 children admitted in the PICU, our findings align with prior research, revealing a consistent trend of decreasing HR with increasing patient age, confirming the inverse correlation. Furthermore, a thorough analysis identifies Gradient Boosting Machines (GBM) implemented with Quantile regression (QR) as the most fitting model, effectively capturing the non-linear relationship between HR, BT, and age. Through testing the HR prediction model based on age and BT, the predictive model between the 5th and 95th percentiles accurately demonstrates the declining trend of HR with age, while HR increases with BT. Based on that, we have developed a user-friendly interface tailored to generate HR predictions at different percentiles based on three key input

parameters : current HR, current BT, and patient's age. The resulting output lets caregivers quickly determine whether a patient's HR falls within or outside the normal range, facilitating informed clinical decision-making. Thus, our results challenge previous studies' presumed direct linear association between HR and BT. *Conclusion :* This study contributes to comprehending the non-linear dynamics between HR, BT, and age in critically ill children with the chosen ML model but also challenges established assumptions about the linear relationship between HR and BT. *Significance :* These findings emphasize the importance of reconsidering traditional assumptions in clinical contexts, potentially changing approaches to understanding physiological indicators, and providing new perspectives for future investigations.

2.2 Introduction

Pediatric Intensive Care Unit (PICU) patients' health requires particular attention and ongoing monitoring (Slusher *et al.*, 2018). Due to their severe conditions or illnesses, these children, particularly those aged 0 to 18 years old, have distinct physiological characteristics requiring special medical evaluation and care (Heneghan *et al.*, 2019). In the PICU of CHUSJ, caregivers often use the Clinical decision support systems (CDSS) in their practice to improve the quality of patient care and outcome (CHUSJ, 2024). In this high-risk environment, healthcare practitioners rely on vital sign monitoring as fundamental indicators of patients' health across all age groups during their hospitalization (Brekke, Puntervoll, Pedersen, Kellett & Brabrand, 2019). These indicators assist in making clinical decisions and facilitate prompt interventions if necessary. Among these vital signs, heart rate (HR) and body temperature (BT) are crucial parameters providing essential information about a child's health, as their relationship can be influenced by age, agitation, stress, infection, shock, physiological distress, or underlying illness (Jensen & Brabrand, 2015; Davies & Maconochie, 2009). Consequently, HR and BT offer invaluable insights for guiding physicians in clinical decision-making (Liu, Yao & Motani, 2019).

Firstly, HR is fundamental in assessing a person's overall cardiac health (Nelson *et al.*, 2020). This metric varies depending on the child's age, as highlighted by Pediatric Advanced

Life Support (PALS) data, where awake patients' reference HR values are age-dependent (Davies & Maconochie, 2009; Fleming *et al.*, 2011). Newborns under 28 days of age typically have an HR ranging from 85 to 205 beats per minute (bpm), while infants and toddlers aged 1 to 24 months fall between 100 and 190 bpm. In children from 2 to 10 years old, the normal HR ranges between 60 and 140 bpm. Adolescents between 10 and 18 years old usually maintain an HR averaging between 60 and 100 bpm. Monitoring patients' HR can be an early indicator of various medical conditions (Daymont *et al.*, 2015). Deviation from the normal HR range can signal underlying health conditions or potential complications. For example, bradycardia, an abnormally low HR, leads to reduced blood flow to organs, leading to dizziness, fatigue, shortness of breath, loss of consciousness, and signs of heart failure (Sidhu & Marine, 2020). Conversely, tachycardia, i.e., high HR, can indicate a severe medical condition, such as shock (Heal *et al.*, 2022).

Additionally, BT regulation is vital for assessing an individual's overall health and reflecting the body's heat production and balance, which are crucial for optimal physiological functions. The regulation of BT is managed by the hypothalamus, a central region within the brain that acts as the body's temperature control center. This process, called thermoregulation, aims to adjust BT based on signals perceived by thermoreceptors in blood and skin. The primary goal is maintaining a normal BT around $37 \pm 0,5$°C, varying slightly in infants and young children. The hypothalamus plays a crucial role in initiating necessary adjustments in temperature fluctuations, whether a decrease or an increase. Extreme temperatures beyond normal ranges indicate health issues : low temperatures (hypothermia) suggest cold responses or medical problems that can potentially lead to severe complications. Elevated temperatures (hyperthermia), triggered by various external factors, such as infection, environmental temperature, or disruptions in the body's thermoregulation system, often signals illness. Consistent temperature checks are important in early illness detection, enabling timely medical interventions. This practice is essential for taking precautionary measures to avert physiological dysfunction and protect organs' structure and function from damage (Walker, Hall & Hurst, 1990).

A distinct pattern is observed in the pediatric population from 0 to 18 years, where HR tends to decrease with age after the initial month. Notably, there is an observed tendency for HR to rise during the first month following birth, reaching its peak before gradually decreasing (Fleming *et al.*, 2011). Insights from studies on hospitalized children in primary care and emergency departments consistently show that BT is an independent factor influencing HR, resulting in an average increase of around 10 bpm per degree centigrade (Daymont *et al.*, 2015; Davies & Maconochie, 2009). More specifically, the studies Thompson *et al.* (2009) and Heal *et al.* (2022) highlighted an age-specific influence of BT on HR. Every 1°C BT increase in children with acute infections correlates with an HR rise ranging from 9.9 to 14.1 bpm (Thompson *et al.*, 2009). In contrast, in children aged 0-16 years old attending urgent and emergency care, the influence of a 1°C increase in HR shows a range of 8.7 to 13.7 bpm, with the observed average being 12.3 bpm (Heal *et al.*, 2022).

In adults admitted to the emergency department, it has been observed that a 1°C increase in BT leads to an approximately 7 bpm increase in HR (Kirschen *et al.*, 2020). In contrast, among acute patients within the emergency department, the results indicate that the group of patients with a high BT, i.e., greater than 37.2°C, exhibited the most significant changes in HR, with an increase of 7.4 ± 0.9 bpm per degree (Jensen & Brabrand, 2015). In critically ill adults admitted to the Intensive Care Unit (ICU), it was observed that within the temperature range of 32.0° to 42.0°C, a linear correlation existed between BT and HR. Specifically, for every 1°C increase within this range, the HR showed a linear increase of 8.35 ± 0.50 bpm ($p < 0.0001$) (Broman *et al.*, 2021).

Regarding the mentioned findings above, the diverse techniques employed to model the relationship between HR and BT in children and adults reflect the complexity of this physiological association. In studies with children, approaches ranged from percentile curves using advanced statistical distributions (Daymont *et al.*, 2015) to quantile regression with polynomial equations (Davies & Maconochie, 2009), centile charts (Thompson *et al.*, 2009), and multiple linear regression models (Heal *et al.*, 2022). Similarly, in adult studies, techniques such as linear regression (Kirschen *et al.*, 2020), linear and multiple variable regression analyses (Jensen & Brabrand, 2015), and multiple linear regression with various covariates (Broman *et al.*, 2021) demonstrated a multifaceted understanding of the HR-BT relationship. These methods illustrate the diverse approaches to understanding the HR-BT relationship in different age groups. The findings highlight the need for age-specific considerations, centile charts, and flexible modeling approaches to improve clinical assessments and guide medical interventions. However, the focus on critically ill children remains significantly limited despite the complexity of their medical conditions. Moreover, acknowledging the existing limitations in which traditional methods may not have captured the complexity of the association, the utilization of Machine Learning (ML) and Deep Learning (DL) techniques would enable a more in-depth analysis to accurately capture the intricate patterns between the two vital signs in critically ill children.

2.3 Materials and Methods

This study was conducted following ethical approval from the research ethics board at CHU Sainte-Justine (CHUSJ). The approved protocol number is 2023-5201. Figure 2.1 represents an overview of the workflow for this study. There are four main steps, including data collection, data preprocessing, ML modeling, and evaluation of the expected output. Those steps are discussed in detail as follows :

2.3.1 Data collection

Since 2015, a high-resolution database has been in operation at CHUSJ, collecting clinical data from patients admitted to the PICU at 1-second to 5-second intervals from monitors. Patients were continuously monitored during their stay until their discharge (Brossier *et al.*, 2018). This project aims to establish a relationship between HR and BT. Patients at CHUSJ PICU were closely monitored for both physiological markers. For BT, continuous monitoring occurred at 30-second intervals, complemented by manual measurements taken every 2-4 hours. The measurement method varied based on the patient's age and included using rectally, esophageal, or axillary temperature probes. HR was monitored using electrodes on the patient's chest, generating an electrocardiogram (ECG). Alternatively, HR could also be obtained using a pulse oximeter attached to the patient's finger, which provides oxygen saturation data and HR measurements.

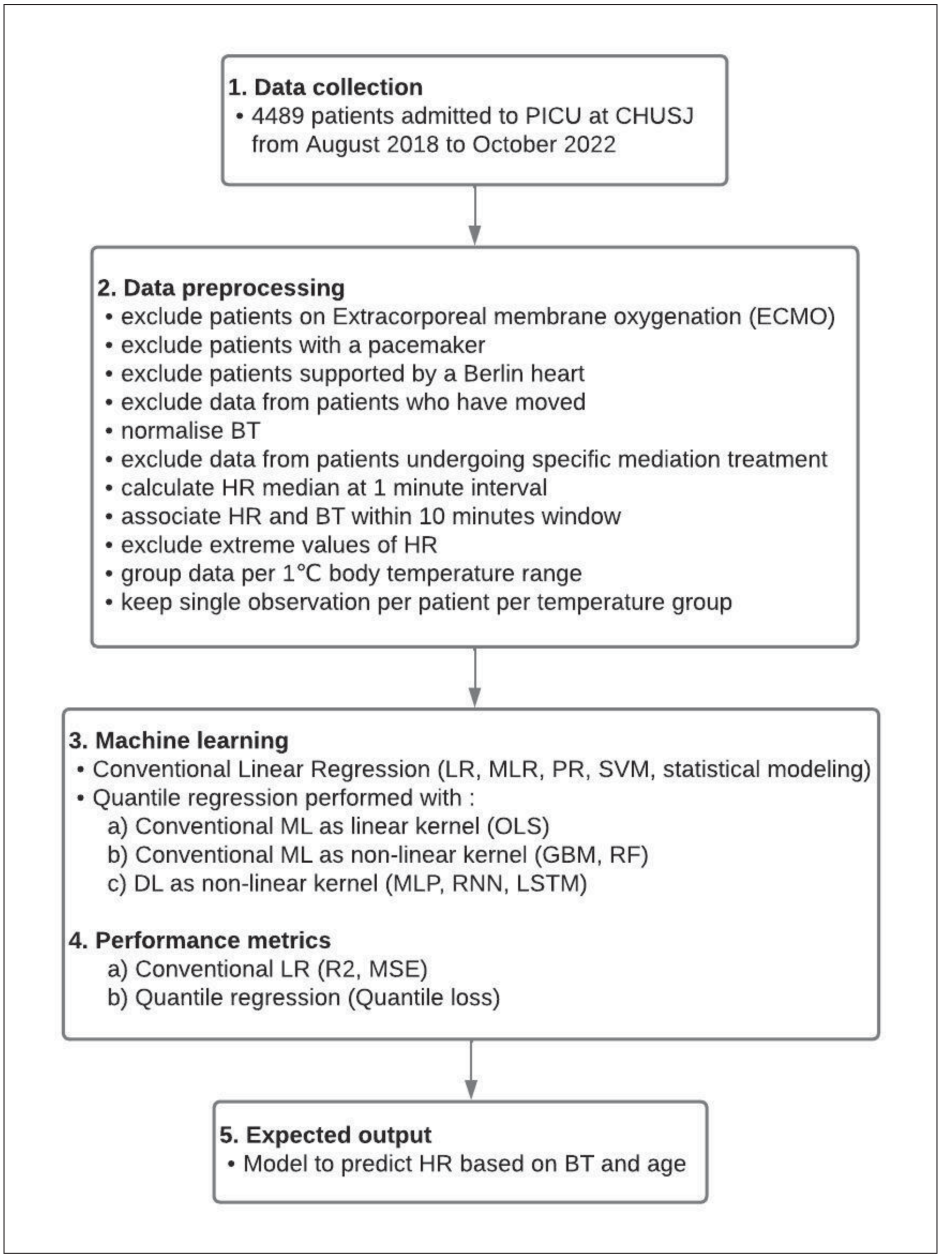

Figure 2.1 Workflow to model the relationship between HR and BT

Children from 0 to 18 years old who were admitted to the PICU between August 2018 and October 2022 with HR and BT records were included in the study. Certain patient groups were excluded from the study in this population to avoid potential confounding factors that interact with BT and HR values. Therefore, removing these data points was essential to achieve accurate modeling. Patients on extracorporeal membrane oxygenation (ECMO), with a pacemaker, or supported by a Berlin heart were excluded. By excluding those patients, our data extraction process yielded information from 4,007 patients admitted between August 2018 and October 2022. From this patient cohort, we extracted patient age at admission, 4 days (96 hours) of HR and BT (value, temperature site, measurement type such as continuous or manual) data along with the corresponding date and time of acquisition, comfort scores and specific medication treatment with the day when the drug treatment was finished.

2.3.2 Data preprocessing

Data preprocessing is a fundamental initial step in preparing patient data for the ML algorithm. Effective data preprocessing ensures data quality issues that can impact the validity of any conclusions drawn (Kinaneva *et al.*, 2021). To get better reliability of subsequent insights, the process involves the following tasks :

2.3.2.1 Exclude data from patients who have moved

Child's movements, including when a patient is restless, crying, or screaming, were excluded from the study. The analysis of the following comfort scores assisted in identifying and excluding data from patients who have moved :

1. **Cornell Assessment of Pediatric Delirium (CAPD)** scale was used in PICU for invasively ventilated children who have fluctuations in awareness, attention, and cognition (Cloedt *et al.*, 2021). The evaluation had 8 questions, and each answer was associated with a score between 0 and 4. The total of these scores determined the outcome ; delirium would be absent if the scores were less than 9.
2. **Comfort Behavior (Comfort B)** was used to assess pain in ventilated and sedated patients (Amigoni *et al.*, 2022). The score involved observing 6 behaviors (awakening, agitation, ventilation, movement, facial expression, muscle tone) rated on a scale of 1 to 5 to determine the perceived pain level. A total score between 11 to 17 indicated a normal score where the patient had no pain.

3. **FLACC (Face, Legs, Activity, Cry, Consolability)** scale was used to evaluate pain in noninvasive patients under 6 years (Cloedt *et al.*, 2021). Each behavior was scored on a scale from 0 to 2, and patients were included in our study if they had a total score between 0 and 3. This range indicated the absence of pain or mild pain.
4. **revised FLACC (r-FLACC)** was used for patients with intellectual disability (Cloedt *et al.*, 2021). The evaluation was executed the same way as the FLACC scale.
5. **Visual numeric Scale (VNS)** was used to evaluate and monitor pain for patients over 6 years with the ability to communicate (Amigoni *et al.*, 2022; Cloedt *et al.*, 2021). The patient evaluated the pain on a scale of 10, with a score between 0 and 3 indicating the absence of pain or mild pain.
6. **Richmond Agitation-Sedation Scale (RASS)** was a scale used to evaluate agitation and sedation (Cloedt *et al.*, 2021). We only kept data with scores between -5 and +1, which signified instances of physical and verbal stimulation.

Based on scores extracted from the database, we assigned movement or not based on the score. Afterward, we associated the scores with the nearest date-time values of BT value since it was monitored at a lower frequency (hours) than HR (seconds). If any of the scores indicated the presence of movement, we excluded the data associated with those movement instances to work with data from calm and non-moving patients.

2.3.2.2 Normalize body temperature

We normalized the temperature data, specifically for measurements obtained from the axillary site, to ensure consistency and accuracy in our analysis. The interpretation of axillary temperatures was underestimated by approximately 0.5°C compared to other methods. Temperature documentation in the PICU was done by recording the actual temperature value displayed on the thermometer. The site from which the temperature was taken (oral, axillary, or rectal) was also noted. Among these methods, rectal temperature measurement was usually considered the most precise (Dolibog, Pietrzyk, Kierszniok & Pawlicki, 2022).

2.3.2.3 Exclude data from patients undergoing specific medication treatment

Patients in the PICU who received Dexmedetomidine and medication affecting HR were only included once their medication treatment was completed. Specifically, medications used to treat heart conditions that slow down HR included antiarrhythmics, beta-blockers, calcium channel blockers, digoxin, and ivabradine (Meyer, Rambod & LeWinter, 2018; King, Goyal, Grigorova & Hashmi, 2018). Conversely, medications that increased HR included Dobutamine, Dopamine, Epinephrine, Milrinone, Norepinephrine (or Noradrenaline), and Salbutamol. To exclude the medication administration period, we excluded data when the monitored timestamp of vital signs coincided with the medication administration.

2.3.2.4 Calculate heart rate median at 1-minute interval

In the PICU, HR values were recorded initially every second for all patients. Given the high frequency of measurements, we simplified the data volume by doing data aggregation. More specifically, calculating the median HR at one-minute intervals made the original high-frequency HR data more manageable and insightful.

2.3.2.5 Associate HR and BT within 10 minutes window

Establishing the association between HR and BT was important as it provided valuable insights into the patient's physiological response. Since HR and BT were monitored at different PICU intervals (seconds vs. hours), we associated these two variables by calculating the median of HR measurements within a 10-minute window, more precisely, within ± 5 minutes of each BT timestamp.

2.3.2.6 Exclude extreme values of heart rate

Extreme HR measurements—values lower than 30 or higher than 240 bpm—were excluded from the dataset. We hypothesized that these numbers could result from unusual clinical diseases or data entry errors, which could have introduced inaccuracies in the analysis. By removing these outliers, we wanted to ensure our dataset was more resilient and reliable. This would have allowed us to base future analysis and modeling efforts on a more accurate depiction of physiological parameters within the target population.

2.3.2.7 Group data per 1°C body temperature range

We segmented the data into temperature ranges of 1 degree Celsius (°C) each to conduct specific temperature value analyses. This temperature-based segmentation created groups ranging from 33°C to 33.9°C up to 40°C to 40.9°C. By doing so, we performed detailed investigations into how patient's physiological responses vary across different temperature ranges, providing insights that could be valuable for clinical and research purposes.

2.3.2.8 Keep single observation per patient

To ensure the integrity and balance of our dataset, we addressed the initial variability in the number of data points attributed to each patient. Initially, there was a substantial variance in the volume of data for each patient. To rectify this imbalance, we implemented a data reduction strategy. We preserved only 1 observation for each patient per temperature group to maintain meaningful and representative data. This practice simplified our dataset and ensured each patient's contribution to the analysis was meaningful and equitable.

After preprocessing, our dataset comprised 4462 pairs of HR-BT values represented in Table 2.1. The values were organized based on BT values, where we used temperature grouping with 1-degree increments. This decision allows for a more granular representation of temperature variations and makes it easier for the ML algorithm to identify patterns in the data (Kinaneva *et al.*, 2021). Moreover, the table provides a breakdown of patient counts according to the patient's age, offering additional insights into the age distribution within the dataset. The age groups include newborn (0-28 days), infant (29 days - 1 year), toddler (1-2 years), child (2-12 years) and teenager (12-18 years). This meticulous grouping strategy corresponds to the Food and Drug Administration (FDA) standard age categorization, with a more detailed grouping specifically for patients aged 1 to 2 years (U.S. Food and Drug Administration, 2024). It also facilitates a more nuanced analysis, considering temperature variations and age-specific patterns in pediatric patients.

Tableau 2.1 Number of observations for each body temperature category by age group following data preprocessing

BT range (°C)	Newborn	Infant	Toddler	Child	Teenager	Total
33-33.9	2	2	0	1	1	6
34-34.9	8	3	0	4	2	17
35-35.9	10	15	3	18	13	59
36-36.9	110	335	139	640	391	1615
37-37.9	136	442	201	752	420	1951
38-38.9	48	168	53	243	117	629
39-39.9	5	28	13	78	28	152
40-40.9	0	3	2	21	7	33

2.3.3 Machine Learning

Following the preprocessing steps, the objective is to capture the intricate relationship between HR and BT in critically ill pediatric patients. We will validate this finding with our data by employing conventional linear regression models based on previous studies highlighting linear relationships. For this study, four popular algorithms were used for modeling the linear relationship Kinaneva *et al.* (2021) :

2.3.3.1 Conventional Linear Regression

(a) **Linear Regression (LR)** is used to determine the best linear function that fits a given set of input-output pairs (Kinaneva *et al.*, 2021). This approach was also used by Kirschen, Singer, Thode Jr, & Singer, 2020 and Jensen & Brabrand, 2015 where they respectively observed that a 1°C rise in BT would cause a 7 bpm and a 7.4 ± 0.9 bpm increase in HR among adults admitted to the emergency department (Kirschen *et al.*, 2020; Jensen & Brabrand, 2015). The limitation of this technique is only one independent variable can be used to predict the dependent variable, making this approach less accurate for prediction. (Kinaneva *et al.*, 2021).

(b) **Multiple Linear Regression (MLR)** is also used to build a linear model to predict the dependent variable related to one or many independent variables, which makes this technique a better prediction model than the linear regression (Kirschen *et al.*, 2020). This technique was used by Heal et al., 2022, Jensen & Brabrand, 2015 and Broman, Vincent, Ronco, Hansson, & Bell, 2021 where they all concluded in a linear change between HR, BT and age (Heal *et al.*, 2022; Jensen & Brabrand, 2015; Broman *et al.*, 2021).

(c) **Polynomial Regression (PR)** with first degree, is a linear regression equation. The first-degree polynomial, often called simple LR, considers terms up to the first power, resulting in a model where the response variable is a linear function of the predictors (Kinaneva *et al.*, 2021).

(d) **Support Vector Machine (SVM)** can be used for both classification and regression problems. In this work, we employed the linear kernel, and the objective was to fit as many data points as possible to the hyperplane line inside the demarcation lines, known as the decision boundaries. This approach's strength is its excellent prediction accuracy and robustness against outliers. However, it does not attempt to minimize the errors between the true and predicted values, in contrast to other regression algorithms (Kinaneva *et al.*, 2021).

(e) **Statistical modeling** approach by Davies & Maconochie, 2009 enabled them to predict HR at different quantiles, leading to the conclusion that "BT serves as an independent determinant of HR, resulting in an approximate increase of 10 bpm per degree centigrade" (Davies & Maconochie, 2009). In our study, we used their established equation to determine its coefficients, then evaluated its effectiveness in predicting HR with our data (Davies & Maconochie, 2009). Their statistical modeling is shown below :

$$\text{Expected HR value} = \text{BT} \cdot a + \text{Age} \cdot b + (\text{Age}^2) \cdot c + \text{constant} \tag{2.1}$$

where BT is the body temperature in °C and Age is the age in month (Davies & Maconochie, 2009).

2.3.3.2 Quantile regression

We incorporated Quantile regression (QR) into our analysis for a more comprehensive exploration, combined with various traditional ML algorithms and DL models. This method allowed us to go beyond linear assumptions and enhanced our ability to uncover linear and non-linear patterns in our dataset. We also included interaction terms BT and age to enhance the accuracy of the predictive model for HR and provide a more comprehensive understanding of the dynamic.

QR is a statistical method used to estimate the response variable at various quantiles (e.g., 0.10, 0.25, 0.50, 0.75, 0.90). Its primary purpose is to analyze the impact of predictor variables (independent variable) on the output variable (dependent variable) across these quantiles. Unlike traditional regression methods, such as Least squares regression, which focus on estimating the mean, QR can offer insights into how the predictors influence various parts of the response distribution, making it valuable in situations where the relationship is not uniform across all quantiles and suitable for capturing a broader range of information about the response variable (Patidar, Wadhvani, Shukla, Gupta & Gyanchandani, 2023). This method is typically utilized when the assumptions of linear regression are unmet. One of the advantages of QR lies in its robustness, as it is less sensitive to outliers compared to the least squares method. This robustness enhances the reliability of the technique in the presence of outliers. Additionally, QR offers flexibility by enabling the capture of the entire distribution of the outcome variables, providing a more comprehensive view of the relationship between variables. Moreover, it addresses the issues related to heteroscedasticity, where the variance of the dependent variable varies differently depending on the levels of the independent variable. This implies that the variance of residuals is not constant across all levels of the response variable (Patidar *et al.*, 2023). Another benefit of using QR is that we may customize the kernel, which allows us to improve our capacity to identify and comprehend subtleties in the relationships between variables. Because of its adaptability, we continue to analyze three different kernels : conventional ML as a linear kernel, conventional ML as a non-linear kernel, and DL as a non-linear kernel.

(a) Conventional ML as a linear kernel

   (i) **Ordinary Least Squares (OLS)** is utilized to model and estimate the coefficients of a linear relationship between variables, particularly when the assumed relationship is linear. OLS aims to comprehend the correlation between variables and make predictions while minimizing the sum of all squared, also called the Residual sum of squares (RSS), differences between observed and predicted values. This method proves efficient in providing accurate parameter estimates when the assumption of linearity holds. It also offers interpretability where the coefficients present clear insights into the relationship between the variables (Hutcheson & Moutinho, 2011).

(b) Conventional ML as a non-linear kernel

   (i) **Gradient Boosting Machine (GBM)** creates a predictive model in the form of a decision tree, where each tree in the ensemble corrects the errors of its predecessor, leading to an overall model with enhanced accuracy and robustness. The primary objective of GBM is to generate a predictive model capable of capturing complex relationships in the data. This versatile technique can be applied to both regression and classification problems. One of its key strengths lies in its iterative improvement process, where subsequent trees focus on addressing the residuals left by previous ones. Its iterative and sequential construction allows it to capture and model complex, non-linear interactions between variables. This flexibility makes GBM a valuable tool for tasks where the underlying relationships may not follow a simple linear structure. Some notable advantages of GBM include high predictive accuracy, the capability to handle both linear and non-linear relationships effectively, and robustness against overfitting. The model's ability to learn from its mistakes and continuously refine its predictions makes it a valuable tool for tasks requiring precision and adaptability in the face of complex data structures (Fafalios, Charonyktakis & Tsamardinos, 2020; Aziz *et al.*, 2020; Boehmke & Greenwell, 2019).

(ii) **Random Forest (RF)** constructs many decision trees, each built on a subset of the data during training. Consequently, the output represents these trees' mean or average prediction for regression problems. Each tree focuses on a specific subset, and the final prediction aggregates these individual tree predictions. The algorithm offers several benefits : flexibility to handle regression and classification problems, robustness against overfitting compared to decision trees, ability to highlight feature importance for better predictive performance, effectiveness in capturing complex relationships and non-linear patterns, and reduced sensitivity to outliers (Cutler, Cutler & Stevens, 2012).

(c) DL as a non-linear kernel

(i) **Recurrent Neural Network (RNN)** is designed to discover patterns in sequential data, making them suitable for time series analysis and natural language processing. Their fundamental advantage lies in their ability to use their collection of previous inputs to make real-time decisions by doing the same task on each sequence element. This model's incapacity to provide background knowledge over an extended period of time is one of its limitations (Sivamohan, Sridhar & Krishnaveni, 2021).

(ii) **Long Short-Term Memory (LSTM)**, an advanced form of RNN, addresses the issue of learning long-term dependencies. Its unique architecture incorporates memory cells, which are capable of maintaining information for extended periods. The model is able to store and retrieve data selectively over an extended period of time due to the memory cells' usage of three gates—forget, input, and output gates—to control information flow. This makes LSTMs highly effective in tasks requiring understanding context over extended periods (Sivamohan *et al.*, 2021; Saha & Senapati, 2020; Saxena, 2024).

(iii) **Multilayer Perceptron (MLP)** is characterized by three layers (input, hidden, and output layers) of interconnected nodes (neurons), where each node in one layer is linked to every node in the next layer with associated weights. Also known as a supplement of feed forwards NN, the data moves in one direction from the input, hidden to the output layer. The multiple hidden layers represent the computational engine of MLP. It facilitates feature learning, allowing the network to acquire hierarchical representations of data and capture intricate patterns and features due to their nonlinear characteristics. Moreover, The MLP's adaptability and effectiveness make it a popular choice for various ML applications, including regression and classification (Molina Estren, De la Hoz Manotas & Mendoza Palechor, 2021).

2.3.4 Performance metrics

The following performance metrics were used to assess the effectiveness of ML and DL models. We used R-squared and Mean square errors to evaluate conventional linear regression. While QR models were evaluated using quantile loss. These metrics provided a comprehensive evaluation of the models' performance, offering insights into their ability to predict and capture the underlying patterns within the data. Each metric contributed to a nuanced understanding of the model's accuracy for the regression task (Varoquaux & Colliot, 2023).

- **R-squared (R2)**, or the coefficient of determination, represents "the proportion of variance in the dependent variable (output) that is predictable from the independent variables (input)" (Chicco, Warrens & Jurman, 2021). The interpretation of R2 provides a quantitative measure of the quality fit. Potentially ranging from 0 to 1, an R2 value near 1 indicates that the model explains all of the dependent variable's variability, signifying a robust fit. In contrast, an R2 value nearing 0 indicates that the model fails to explain the variability in the dependent variable, implying a less effective fit (Keer, Lohiya & Chouhan, 2023). The R2 equation is defined below :

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}{\sum_{i=1}^{n}(Y_i - \tilde{Y})^2} \tag{2.2}$$

where n is the number of observations, Y_i is the true value, $\hat{Y}_i$ is the predicted value and $\tilde{Y}$ is the mean of Y values. More precisely, the numerator is the sum of the squared residual (SSR), representing the difference between the actual and predicted values. The denominator is the total variations of the sum of squares, representing the sum of the distance between the data and the mean all squared (Keer *et al.*, 2023).

- **Mean Square Error (MSE)** measures the average squared difference between the true and the predicted values. Being only a positive value, the interpretation of the MSE value is as follows : a lower MSE signifies that the predicted values exhibit closer proximity to the actual values, reflecting an enhanced overall fit. This metric provides a standardized measure for evaluating regression models' precision and accuracy, facilitating straightforward comparisons between different models (Tyagi, Rane, Manry *et al.*, 2022; Rane, Tyagi, Malalur, Shinge & Manry, 2023). The MSE equation is defined below :

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \tag{2.3}$$

where n is the number of observations, Y_i is the true value and $\hat{Y}_i$ is the predicted value. (Tyagi *et al.*, 2022)

- **Quantile Loss (QL)**, also known as Pinball Loss, is a metric used in QR to calculate the performance of conditional quantiles, providing insight into how well a model captures the distribution of the data (Steinwart & Christmann, 2011). Unlike other ML algorithms, R2 is not a good metric to evaluate performance since it is not based on distribution assumptions (Machado & Silva, 2013). A reminder that QR is a statistical method that aims to model the response variable's conditional distribution through different quantiles, allowing us to have information on the entire distribution, not just the mean. To interpret QL results, a low QL value means a superior performance from the model, suggesting that the predicted values closely align with the actual values at the designated quantile (Narayan, Wang, Canini & Gupta). The QL equation is shown below :

$$QL_\tau(y, \hat{y}) = max(\tau(y - \hat{y}), (\tau - 1)(y - \hat{y})) \tag{2.4}$$

where τ is the quantile level, y is the true value, $\hat{y}$ is the predicted value (Narayan *et al.*). To validate the performance of quantile regression for each model, it is necessary to compute the total quantile loss, achieved by calculating the average quantile loss across all quantiles. This approach enables a robust assessment of the model's efficacy across the entire distribution, ensuring a comprehensive performance analysis of all quantiles within a model (Alutaibi & Ganti, 2020).

In summary, the ultimate goal is to identify patterns and associations and develop a robust predictive model. The model aims to assist healthcare professionals in anticipating changes in HR based on variations in BT, age, and quantile of interest. Through the integration of advanced ML methodologies, this study seeks to propel the field of pediatric critical care forward, providing clinicians with actionable insights to tailor interventions and enhance overall patient care in the PICU.

2.4 Results and Discussion

Firstly, our initial findings from the research involve the generation of a graph showing HR concerning age for a temperature range presented in Figure 2.2. Upon analysis, we observe a trend where HR decreases with the patient's age. This observation aligns with the findings presented in the article by the study (Fleming *et al.*, 2011). The graphical representation provides valuable insights into the relationship between age and HR within distinct temperature ranges, highlighting a potential correlation that needs further investigation. This initial exploration sets the foundation for a more in-depth analysis of age-related variations in HR across different BT intervals.

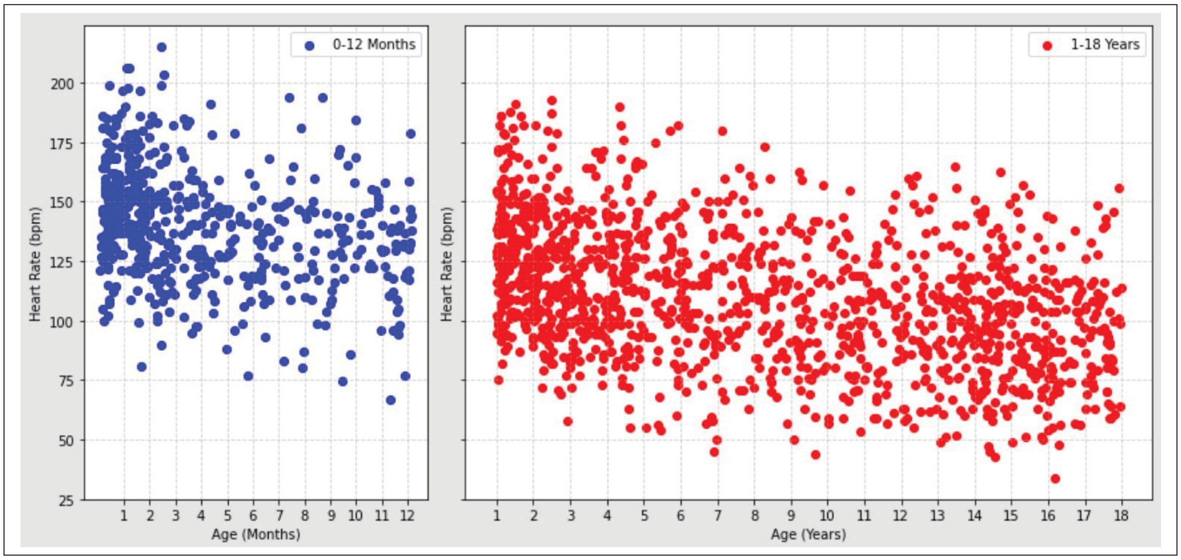

Figure 2.2 Heart rate as a function of age for children from 0-18 years old admitted to the PICU with body temperature between 37 to 37.9°C

Expanding on these insights, we applied ML techniques to uncover subtle patterns and dependencies within our dataset. Each algorithm underwent meticulous hyperparameter tuning process, where parameters such as learning rate, batch size, among other parameters specific to the model's requirements were carefully adjusted before the training process commenced. This meticulous tuning involves a thorough examination and adjustment of these parameters to optimize the model's performance. It includes iteratively fine-tuning each hyperparameter, training the model, and rigorously evaluating its performance until an optimal configuration is achieved. The goal is to enhance the model's effectiveness and accuracy. This meticulous approach to hyperparameter tuning is essential for achieving optimal results and maximizing the model's potential.

Since prior research has consistently underscored the linear association between HR and BT (Daymont *et al.*, 2015; Davies & Maconochie, 2009; Thompson *et al.*, 2009; Heal *et al.*, 2022; Kirschen *et al.*, 2020; Jensen & Brabrand, 2015; Broman *et al.*, 2021), we initially used conventional linear regression models. We started with LR to predict HR based on age for each

BT range. Subsequently, we explored MLR and PR degree 1 to incorporate BT and age as independent variables. Finally, we experimented with SVM with a linear kernel and the statistical model. Examining the outcomes of our analyses, the performances of these traditional linear regression methods in capturing the linear relationship for BT ranging from 37 to 37.9°C are summarized in Table 2.2. From the comparative analysis, we can conclude that there are no clear and obvious linear relations between HR and BT because of significantly small R2 values and a large value of MSE loss. These values suggest that the linear models struggled to account for a substantial portion of the variability in HR based on BT and age. Based on these findings, there may be a potential need for more advanced methodologies to effectively capture the intricacies of the relationship between HR and BT.

Tableau 2.2 Model performance from traditional linear Machine Learning techniques to predict heart rate from children 0-18 years old with body temperature between 33 to 40.9°C

Conventional linear regression	R2	MSE
Linear regression	0.3145	621.1870
Multiple Linear Regression	0.3563	583.2989
Polynomial regression (degree = 1)	0.3563	583.2989
SVM (kernel : linear)	0.3152	620.5312
Statistical model (quantile=0.5)	0.3576	581.2691

Our experimental findings suggest that linear models might not be able to adequately capture the complexity of the relationship observed in critically ill patients. This assertion is supported by the studies (Momo & Morikawa, 2023; Heal, Harvey, Brown, Rowland & Roland, 2023), highlighting the non-linear correlation between HR and BT. Specifically, in Momo & Morikawa (2023) article, the authors criticize the work of Heal *et al.* (2022), who utilized linear regression models to demonstrate a significant increase in HR of 12.3 bpm for every 1°C rise in BT among emergency department patients. Additionally, Momo & Morikawa (2023) underscore the significance of findings from other studies employing non-linear models. These studies reveal a distinct, curve-like increase in HR within the temperature range of 37°C to 38°C, highlighting the intricate relationship between HR and BT (Momo & Morikawa, 2023).

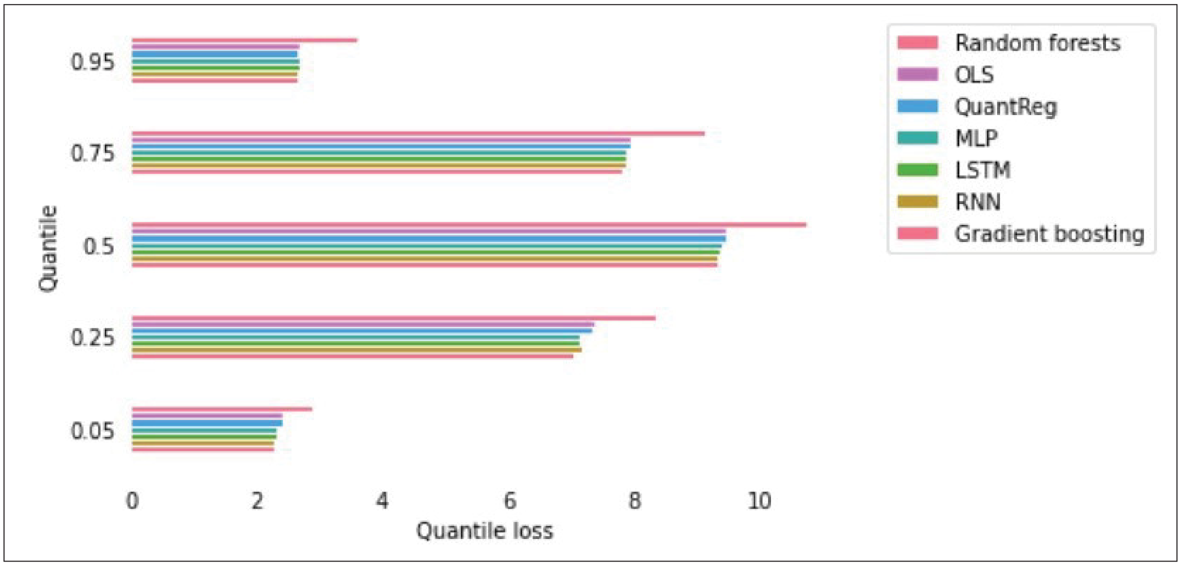

Figure 2.3 Comparison of quantile loss per quantile for each technique for a body temperature range between 33 to 40.9°C from critically Ill patients 0-18 years old from 1 experiment

The authors respond to the previously mentioned critiques in the article by Heal et al. (2023). They acknowledge that employing linear models may not be the most accurate approach and suggest using polynomial regression. They also note that contrary to earlier research suggesting a general 1°C increase correlating with a 10 bpm rise, their findings indicate a 12.3 bpm increase, emphasizing potential variations within specific temperature ranges. This distinction gains particular significance when considering the application of such predictive tools to individual patients in a clinical setting (Heal *et al.*, 2023).

Since traditional linear models do not adequately capture the complex and potentially non-linear relationship, we conducted a comprehensive evaluation using QR performed with ML and DL as a linear and non-linear kernel. Through this, we aim to enhance the depth and precision of our analysis. The advantage of QR lies in its ability to handle data with varying distributions and to provide a more nuanced understanding of the conditional distribution of the response variable across different quantiles (Patidar *et al.*, 2023). This is particularly relevant when the relationship between variables may not be constant across the entire distribution. To evaluate the models with QR, it is unsuitable to use R2, as mentioned in the literature (Machado & Silva, 2013). Instead, it is essential to investigate the quantile loss (QL) for each quantile as the performance metric for QR. The results presented in Figure 2.3 reveal that the lowest QL value is seen at each quantile in QR performed with GBM, showing that the underlying relationship is effectively captured.

To assess the performance of each model with QR, the performance metric is the total quantile loss, representing the overall performance across all quantiles within a model. This metric is obtained by calculating the average QL across all quantiles. The data presented in Table 2.3 detail the average total quantile loss and the standard deviation (SD) for each predictive model derived from the outcomes of five distinct experiments. The best model is once again QR performed with GBM. The model demonstrates superior efficacy by achieving the lowest total quantile loss value. The superior performance of this model suggests its efficacy in handling the complexities in the data, contributing to enhanced predictive capabilities. This advanced method outperforms conventional approaches with linear kernels, such as OLS, RF, and standalone QR. Specifically, the higher total quantile loss result for RF implies potential limitations in its effectiveness within this context. These results underscore the significance of employing advanced ML and DL techniques for capturing nuanced patterns in critical care scenarios, providing valuable insights into the relationships between physiological parameters.

Tableau 2.3 Mean total quantile loss and Standard deviation from 5 experiments for different methods performed with QR with a temperature range between 33 to 40.9°C from critically Ill patients 0-18 years old

Model	Mean total quantile loss ± Standard deviation
GBM	6.5069 ± 5.2507e-05
RNN	6.5633 ± 0.0078
LSTM	6.5990 ± 0.0144
MLP	6.6148 ± 0.0236
OLS	6.6867 ± 0.0
QR	6.6903 ± 0.0
RF	7.6584 ± 0.0

Fig. 2.4 presents the predictive accomplishment of the best-performing model—QR using GBM kernel—highlighting its capacity to capture the complex non-linear relationships at varying quantiles (0.05, 0.25, 0.50, 0.75, 0.95). From top to bottom, the figure sequentially exhibits the model's proficiency in forecasting HR at multiple quantiles, from the 5th to the 95th percentile. This projection is based on patient age, ranging from infancy to nearly 18 years (0-200 months), and BT between 34°C to 40.9°C. The x-axis denotes the patient's age in months, and the y-axis records HR in beats per minute (bpm). The subfigure presents the actual HR data as black dots, with the model's predicted values shown in red, facilitating a straightforward comparison of the observed and predicted HR. This allows for a direct appraisal of the model's precision in replicating the true HR values.

Furthermore, in response to the nature of the wide BT range (from 34°C to 40.9°C), Fig. 2.5 is introduced to deliver enhanced detail concerning the model's predictions, with respect to BT variations. Specifically, the experimental results for HR prediction for a specific quantile (0.05, 0.25, 0.50, 0.75, 0.95) are presented, respectively, in each row. A color gradient alongside each scatter plot translates the spectrum of colors to specific BT values, offering an instant visual guide. The scatter points, color-coded to represent varying BTs, effectively differentiate the HR predictions according to BT variations, thereby enriching the visual representation and enhancing the interpretability of the model's capacity to account for temperature-dependent HR variations. Consequently, analyzing the scatter plots across all the quantiles reveals a pattern : as BT increases, so does the predicted HR, while an inverse relationship is observed with increasing age, where the predicted HR generally declines. This visualization is not merely a reflection of the model's prediction accuracy ; it also communicates critical insights for clinical applications, particularly as it highlights the expected HR values within the commonly encountered 5th to 95th percentile range in a clinical setting.

To enable clinicians to utilize our QR prediction model performed with GBM, we have developed an example of a simple user interface (UI). This UI processes three input parameters : the current HR, BT, and the patient's age. The output shows HR predictions across various percentiles (5th and 95th) tailored to a specific patient, as shown in Figure 2.6. Importantly, our model defines

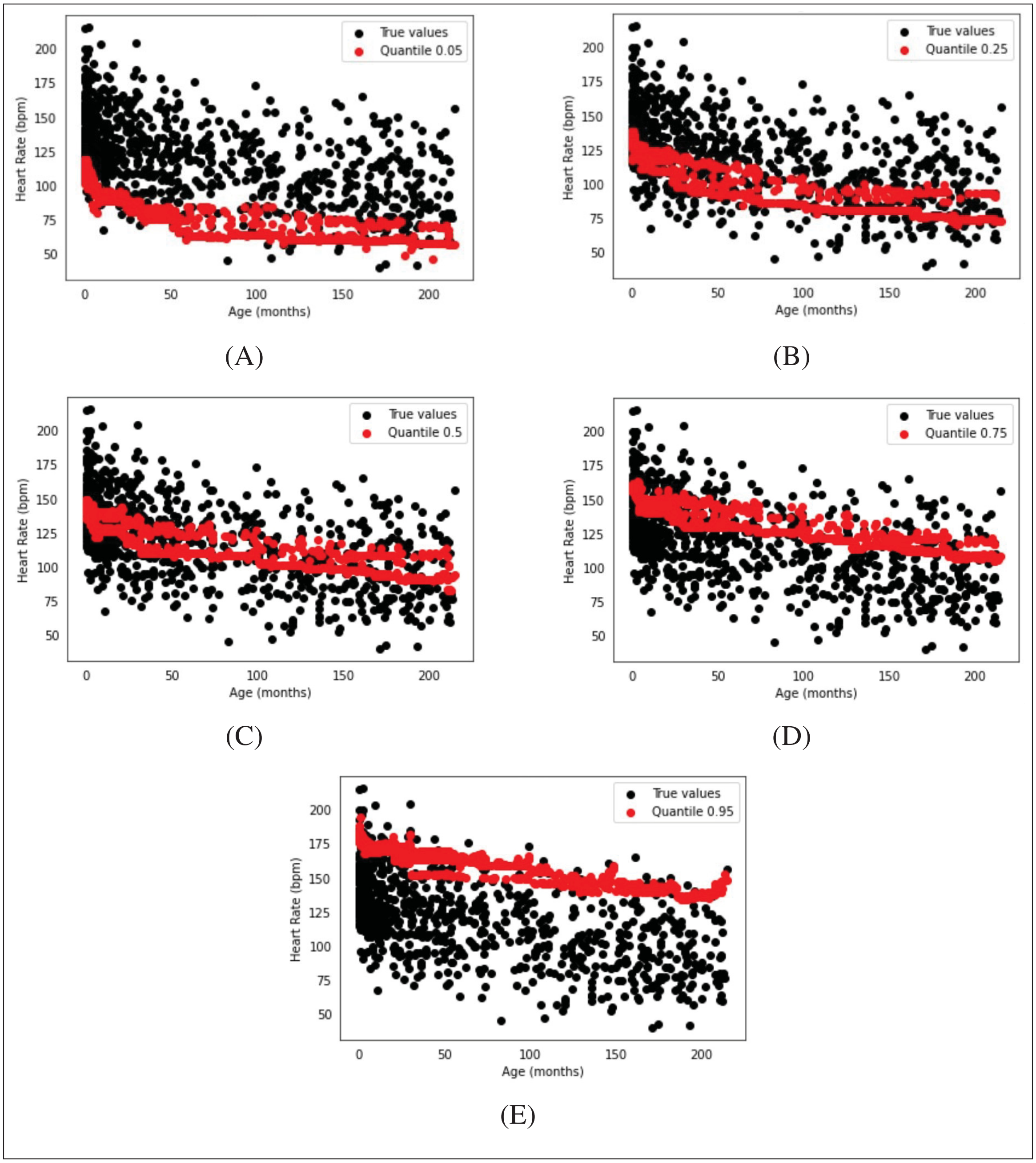

Figure 2.4 QR performed with GBM model shows a non-linear relationship between HR, BT, and age for children 0-18 years old admitted to PICU with a temperature range of 34 to 40.9°C. True values are shown in black, while predictions are shown in red. The analysis is performed at different quantiles, where each row represents a specific quantile, from 0.05 to 0.95. Subfigure (A) illustrates model predictions at quantile 0.05, (B) at quantile 0.25, (C) at quantile 0.50, (D) at quantile 0.75, and (E) at quantile 0.95.

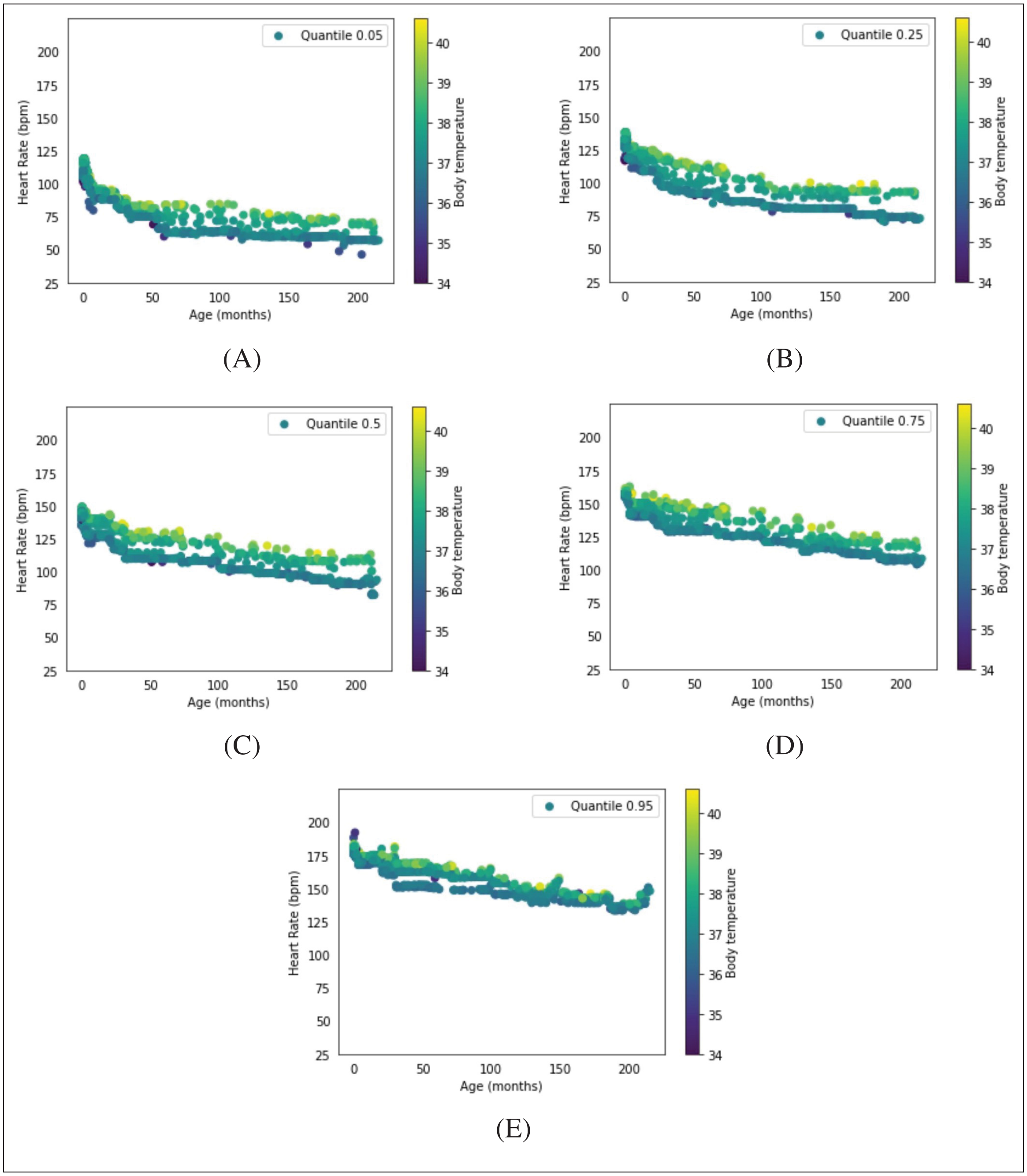

Figure 2.5 Exploration of the HR model predictions influenced by age along the x-axis and BT through variation of 34 to 40.9°C in the color scale for children 0-18 years old admitted to PICU. The analysis is performed at different quantiles, where each row represents a specific quantile, from 0.05 to 0.95. Subfigure (A) illustrates model predictions at quantile 0.05, (B) at quantile 0.25, (C) at quantile 0.50, (D) at quantile 0.75, and (E) at quantile 0.95.

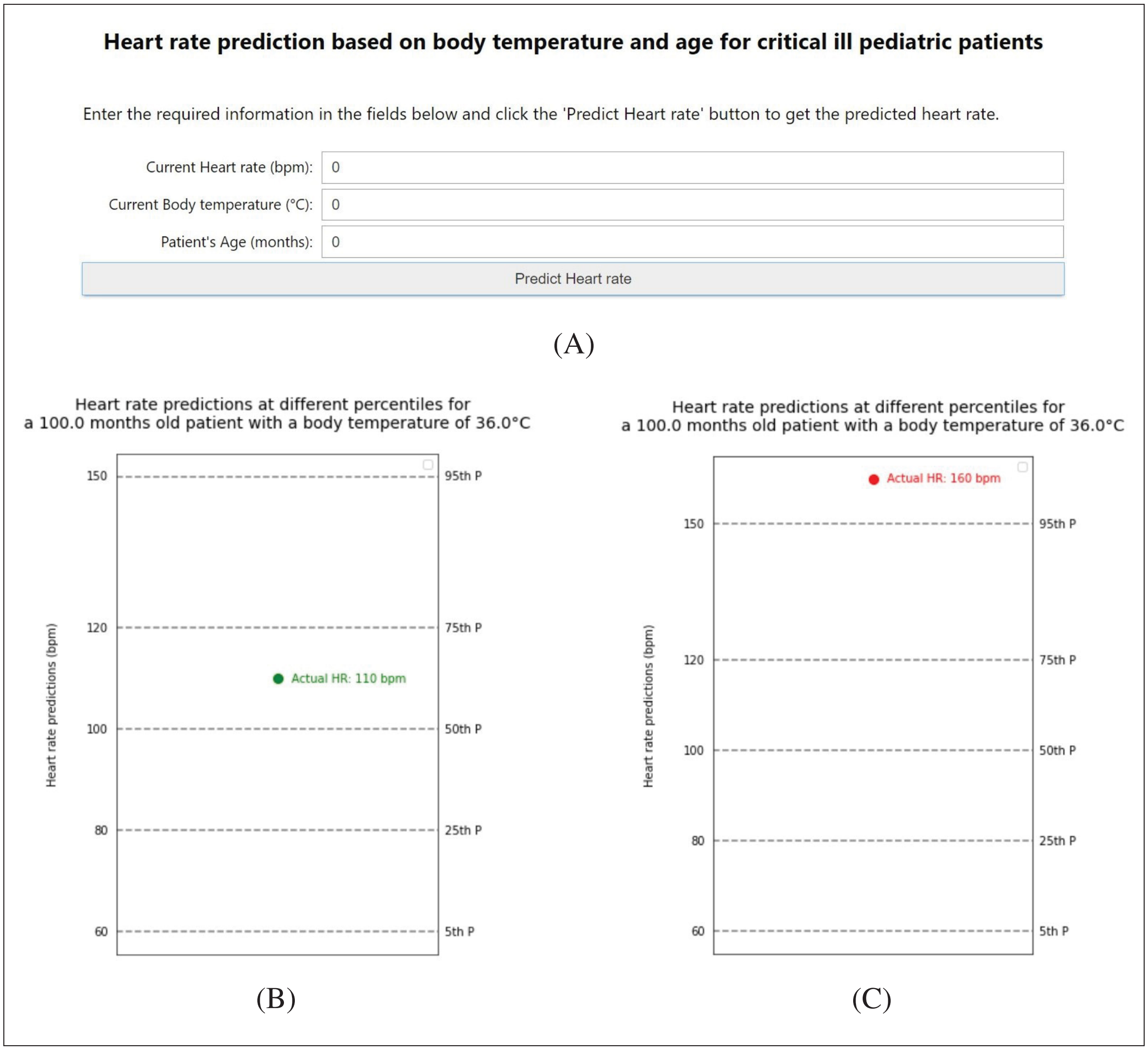

Figure 2.6 HR Predictions at different percentiles (5th, 25th, 50th, 75th, 95th) for a given patient's age and BT will be integrated into the CDSS system (A) User interface featuring three key inputs - current HR, current BT, and patient's age - for HR predictions (B) Example of case scenario with a normal HR is indicated by a green dot, which falls within the normal range defined by the 5th and 95th percentiles (C) Another example of a case scenario shows an abnormal HR, marked by a red dot located outside the normal range

a normal HR range within the 5th to 95th percentile. Within this range, a green dot signifies that the patient's HR falls within the expected parameters. On the other hand, a red dot serves as an immediate visual indicator of deviation from the norm, demanding prompt attention and intervention. As a result, this CDSS can determine in real-time whether the patient's HR is within the predicted range or needs more evaluation, thereby helping caregivers with clinical decision-making.

This predictive model holds immense potential for integration within existing data representation developed by Yakob *et al.* (2024) for the CDSS in the PICU of CHUSJ (Yakob *et al.*, 2024). However, it should be noted that integrating this tool in the PICU of CHUSJ does not require caregivers to manually enter patient information. In fact, the data representation for the CDSS consists of three levels : unit, patient, and system levels. The unit level allows visualization of all admitted patients, while the patient level enables assessment of the patient's status and progress (Yakob *et al.*, 2024). Lastly, the system level presents many "groups of indicators related to human body systems and provides access to decision support tools developed for specific issues involving these systems (Yakob *et al.*, 2024)". Therefore, the patient's information is already integrated into the system automatically. Consequently, our predictive model will be generated and displayed at the system level of the CDSS.

Our model's limitation is that no HR prediction is provided if the inputs fall outside the ranges covered by our dataset. This underscores the importance of ensuring that the input parameters remain within the dataset's scope to obtain accurate predictions. Furthermore, clinicians must evaluate the predictions' interpretation and validation. This highlights the critical role of clinical expertise in assessing and confirming the accuracy and clinical relevance of the predicted HR values in this population.

2.5 Conclusion

In summary, this study represents a comprehensive and innovative approach to understanding the relationship between HR, BT, and age in children within the PICU. By employing a meticulous multi-stage data preprocessing strategy, the research aimed to reveal complex patterns that conventional models might overlook.

The findings of this study align with prior research by confirming the expected downtrend in HR with increasing patient age. However, the nuanced approach of grouping data by temperature rather than age allowed for a more granular exploration. Notably, the performance evaluation of various ML and DL algorithms yielded insightful results. Unlike some earlier studies that suggested linear correlations, conventional linear regression demonstrated limited effectiveness in capturing the linear relationship within the data. On the other hand, QR performed with advanced ML, such as the GBM model, exhibited superior performance, successfully uncovering non-linear relationships across a broad BT range from 33 to 40.9°C. Furthermore, the HR model predictions clearly show a downward HR trend with age and an upward trend with BT between the 5th and 95th percentiles. Based on that model, we created a simple user interface for caregivers. Based on age and BT, they can quickly determine in real-time whether a patient's HR falls within the normal range or not.

These findings have significant implications, highlighting the potential of ML and DL techniques to decode intricate associations in critically ill pediatric patients. The identified model enhances prediction capabilities and holds promise for early detection and developing more personalized and effective therapeutic interventions.

Looking forward, this work suggests promising future directions and areas for improvement. One intriguing prospect involves observing a cohort of subjects upon whom clinicians have implemented interventions guided by the predicted HR model. These observations could involve observing trends and assessing the long-term effects of interventions. Extracting insights from the resulting conditions and outcomes would be interesting in refining future studies. Moreover, if the HR falls outside the 5th and 95th percentiles, the time spent in this range may be associated with bad outcomes. It would be valuable to investigate whether there are treatments that could reduce the duration of time spent in these extremes to enhance patient outcomes. Another direction for future research is to explore the interplay of variables, focusing on gender-based differences, considering that HR tends to be higher in women than men. Finally, incorporating other neural network architectures, such as Convolutional Neural Networks (CNN) or Transformers, could offer valuable insights.

CONCLUSION ET RECOMMANDATIONS

En conclusion, notre étude présente une importance significative dans le domaine des soins intensifs pédiatriques, visant à combler la lacune dans la modélisation prédictive de la FC basée sur la TC et l'âge chez les patients gravement malades âgés de 0 à 18 ans. Notre approche exhaustive a impliqué la collecte de données à partir d'une base de données haute résolution, des étapes méticuleuses de prétraitement des données et l'application de diverses techniques de régression, y compris la régression linéaire conventionnelle et les méthodes d'apprentissage automatique et d'apprentissage profond.

L'objectif principal était de capturer la relation linéaire, comme le soulignaient les études antérieures. Cependant, notre étude a révélé une faible performance de la régression linéaire conventionnelle, avec un faible R2 et un MSE élevé. Par conséquent, l'objectif suivant était d'explorer des techniques plus avancées pour dévoiler la relation complexe, potentiellement non linéaire. Nos résultats soulignent la performance supérieure de QR avec noyau non linéaire, en particulier GBM, dans la modélisation précise de l'interaction dynamique de ces paramètres physiologiques. Ce modèle innovant permet non seulement d'avancer notre compréhension scientifique des dynamiques des soins intensifs, mais fournit également un outil pratique pour les cliniciens. En offrant la possibilité de prédire la FC selon des niveaux spécifiques de TC et d'âge, ce modèle permet aux cliniciens de l'USIP de déterminer si la FC d'un patient se situe dans la plage attendue, leur permettant ainsi de prendre des décisions éclairées et de mettre en place des interventions appropriées pour optimiser les résultats pour les patients.

Bien que les prédictions de nos modèles représentent une avancée notable, il est essentiel de reconnaître certaines limitations et de proposer des pistes de recherche futures. Les futures études pourraient explorer des techniques pour améliorer la précision de la modélisation par nuage de points ou envisager des méthodes de visualisation alternatives pour une meilleure précision. De plus, l'outil développé permet des prédictions de FC basées sur trois entrées clés et sont générées par le modèle QR avec GBM. Cependant, les prédictions doivent être évaluées par le clinicien pour garantir leur précision et leur pertinence pour la prise de décision clinique. Sans oublier l'impact du sexe du patient sur les différences de FC, les efforts de recherche futurs pourraient se pencher sur des considérations spécifiques au genre pour affiner et personnaliser davantage le modèle. Enfin, des efforts de collaboration entre les scientifiques des données, les cliniciens et les chercheurs sont encouragés pour faciliter les améliorations et les affinements continus des modèles prédictifs, améliorant ainsi les stratégies de soins aux patients dans le cadre dynamique de l'USIP.

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