

Machine Learning-Based Prediction of Individualized Drug Dosing in Pediatric Patients Using Clinical and Demographic Parameters

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Abstract

Pediatric drug dosing remains a significant clinical challenge because children exhibit substantial variability in drug absorption, distribution, metabolism, and excretion throughout growth and development. Conventional dosing approaches, which primarily rely on body weight, body surface area, or age-based dosing guidelines, may not adequately account for individual differences in physiological development, organ function, disease severity, concomitant medications, and genetic factors. Machine learning (ML) offers an opportunity to improve individualized drug dosing by integrating clinical, demographic, laboratory, and pharmacokinetic parameters to estimate appropriate dose requirements and predict the likelihood of adverse drug reactions or subtherapeutic exposure.

This review-oriented research paper examines the potential application of ML techniques, including random forest, gradient boosting, support vector regression, artificial neural networks, and ensemble learning, in pediatric dose prediction. Relevant input variables include age, body weight, height, body surface area, gestational age, renal and hepatic function, serum drug concentrations, clinical diagnosis, and concomitant medication use. The manuscript outlines a conceptual framework for collecting clinical data, preprocessing variables, training predictive models, evaluating performance, and integrating model recommendations into clinical decision-making. Particular attention is given to therapeutic drug monitoring, model interpretability, data privacy, population representation, and the distinctive ethical and safety requirements of pediatric research. The proposed framework emphasizes that machine learning should support, rather than replace, clinical judgment and established dosing protocols. Before implementation, predictive models require rigorous external validation, prospective evaluation, and assessment of clinical utility across diverse pediatric populations. When appropriately developed and validated, ML-based approaches may contribute to safer, more precise, and more individualized pharmacotherapy for children.

Keywords: Machine learning; pediatric pharmacology; individualized drug dosing; precision medicine; clinical decision support; pharmacokinetics; therapeutic drug monitoring; artificial intelligence; pediatric patients; dose optimization.

1. Introduction

Individualized drug dosing is an important component of effective and safe pediatric pharmacotherapy. Children are not simply smaller versions of adults; they undergo continuous developmental changes that influence the pharmacokinetic and pharmacodynamic behavior of medications. Age-dependent variations in gastric physiology, body-water composition, plasma protein binding, hepatic enzyme activity, renal filtration, and drug transporter expression can significantly affect drug exposure and treatment response [1–4].

In routine clinical practice, pediatric doses are commonly calculated using body weight, body surface area, age, or a combination of these parameters. Although these methods provide practical starting points, they may not fully capture the variability between children of the same age or weight. Two patients receiving identical weight-adjusted doses may experience different drug concentrations, therapeutic outcomes, or adverse effects because of differences in organ function, developmental maturity, underlying illness, or drug interactions.

The increasing availability of electronic health records (EHRs), laboratory information systems, and therapeutic drug monitoring data has created opportunities to develop data-driven approaches to dose optimization. Machine learning is a branch of artificial intelligence that identifies patterns in data and uses them to make predictions for previously unseen observations. In clinical pharmacology, ML algorithms can examine complex, nonlinear relationships among demographic characteristics, clinical measurements, medication exposure, and treatment outcomes.

For example, a model developed for a specific medication could estimate an initial dose or predict the probability that a proposed dose will produce a drug concentration within a predefined therapeutic range. Such estimates may be particularly useful when conventional dosing equations perform poorly or when multiple patient characteristics jointly influence drug clearance.

However, pediatric dosing applications require special caution. A model that performs well in adults cannot automatically be assumed to be suitable for children, and a model developed for one pediatric age group or medication may not generalize to another. Accordingly, the development of individualized dosing algorithms must incorporate pediatric pharmacology, sound statistical methodology, clinical validation, and appropriate oversight.

This paper presents a review-oriented framework for using clinical and demographic parameters in ML-based pediatric dose prediction. It discusses candidate algorithms, relevant variables, model development, validation strategies, clinical applications, and barriers to implementation.

2. Aim and Objectives

Aim: To examine how machine learning can support individualized drug-dose prediction in pediatric patients using clinical, demographic, and pharmacological parameters.

1. Identify demographic and clinical variables relevant to pediatric drug-dose prediction.
2. Describe ML algorithms suitable for estimating individualized dosing requirements.
3. Develop a conceptual workflow for model training, validation, and clinical integration.
4. Discuss potential applications in therapeutic drug monitoring and medication safety.
5. Identify methodological, ethical, and clinical challenges associated with implementing ML-based dosing systems.

3. Review Methodology

This study employs an extensive narrative literature review approach to investigate the role of machine learning (ML) in predicting individualized drug dosing in pediatric patients using clinical, demographic, physiological, and pharmacokinetic parameters. The primary objective of the review is to examine how data-driven computational techniques can support the development of accurate, personalized, and clinically relevant dosing strategies for children across different developmental stages. Pediatric drug dosing presents considerable challenges because children differ from adults in body composition, organ maturity, drug absorption, distribution, metabolism, and excretion. Furthermore, these characteristics change continuously from the neonatal period through infancy, childhood, and adolescence. Consequently, conventional weight-based dosing approaches may not always adequately account for individual variations in drug exposure, therapeutic response, and the risk of adverse drug reactions. In this context, the review focuses on the potential contribution of ML algorithms to improving dose prediction, identifying clinically significant predictors of drug disposition, and supporting precision pharmacotherapy in pediatric populations.

Relevant scientific literature should be identified through structured searches of electronic databases, including PubMed/MEDLINE, Scopus, Web of Science, and Google Scholar. Additional information may be obtained from the reference lists of relevant publications and authoritative regulatory documents addressing pediatric drug development, pharmacokinetic modelling, therapeutic drug monitoring, and individualized dosing. The search strategy should combine keywords and related terms using Boolean operators such as AND and OR. Representative search terms include “machine learning,” “artificial intelligence,” “pediatric drug dosing,” “individualized drug dosing,” “precision dosing,” “pediatric pharmacokinetics,” “pharmacokinetic modelling,” “population pharmacokinetics,” “therapeutic drug monitoring,” “dose prediction,” “clinical parameters,” “demographic variables,” and “model-informed precision dosing.” Example search combinations include “machine learning AND pediatric drug dosing,” “artificial intelligence AND pediatric pharmacokinetics,” “individualized dosing AND clinical parameters,” and “precision dosing AND therapeutic drug monitoring.” Where appropriate, synonyms and drug-

specific terms should also be incorporated to identify studies examining the prediction of drug concentrations, dose requirements, treatment response, and toxicity in pediatric patients.

The literature considered relevant to this review should encompass original research articles, clinical pharmacokinetic studies, retrospective and prospective observational studies, model-development and validation studies, systematic reviews, narrative reviews, and relevant clinical or regulatory guidance documents. Priority should be given to peer-reviewed publications that directly investigate pediatric populations, ML-based dose prediction, pharmacokinetic variability, or the integration of clinical data into individualized treatment strategies. Studies involving adults may also be considered when they provide important methodological insights into ML algorithms or model-informed precision dosing, although their findings should not be assumed to be directly applicable to children. Publications addressing neonatal and pediatric intensive care, antimicrobial therapy, immunosuppressive medications, anticonvulsants, and other drugs requiring careful dose individualization may provide useful examples of clinical applications. Both established pharmacometric approaches and emerging ML-based techniques should be examined to understand their respective advantages, limitations, and potential for integration into clinical practice.

The review should pay particular attention to the clinical, demographic, laboratory, and pharmacokinetic variables used as predictors in ML models. Demographic parameters may include chronological age, gestational age, sex, and developmental stage, whereas anthropometric parameters may include body weight, height, body surface area, and body composition when available. Clinical variables may include the primary diagnosis, disease severity, comorbidities, renal and hepatic function, nutritional status, and relevant physiological measurements. Laboratory parameters, such as serum creatinine, liver function markers, albumin concentrations, and inflammatory biomarkers, may also influence drug disposition or treatment response, depending on the medication under investigation. In addition, concomitant medications, dosage history, administration route, sampling time, previous therapeutic drug concentrations, and pharmacogenetic information may be important predictors where these data are available. The relevance of each variable should be assessed in relation to the drug's pharmacological properties, the patient's developmental characteristics, and the clinical outcome being predicted.

A further component of the review involves examining the ML algorithms used for individualized pediatric dose prediction. These may include linear and regularized regression models, decision trees, random forests, support vector machines, gradient-boosting methods, artificial neural networks, and deep-learning architectures. Their applications may range from predicting drug clearance and concentration-time profiles to estimating the probability of achieving therapeutic drug targets or identifying patients at increased risk of toxicity. The review should also consider hybrid approaches that combine ML algorithms with population pharmacokinetic models, physiologically based pharmacokinetic models, or Bayesian forecasting methods. Such approaches may be particularly valuable because they can integrate prior pharmacological knowledge with patient-specific observations. Where studies provide sufficient information, the review should compare model performance using reported measures such as mean absolute error, root mean squared error, coefficient of determination, prediction bias, calibration, and the proportion of predictions falling within clinically acceptable limits. Performance measures should be interpreted in the context of the drug, patient population, dataset, and intended clinical application rather than compared indiscriminately across unrelated studies.

The methodological quality and clinical applicability of the identified studies should also be considered. Important aspects include sample size, completeness of clinical data, handling of missing values, selection of predictor variables, prevention of data leakage, and the use of appropriate training, validation, and test datasets. Particular attention should be given to whether models were evaluated using independent patient cohorts or external datasets, as performance measured only on the development dataset may overestimate their ability to generalize to new patients. Potential biases arising from imbalanced datasets, differences between hospitals, variation in laboratory measurements, and underrepresentation of specific pediatric age groups should also be examined. For example, a model developed predominantly using data from older children may not perform reliably in premature neonates because their physiological characteristics and drug-handling mechanisms differ substantially. Similarly, a model trained using data from one institution may require additional validation before being implemented in another healthcare setting.

In addition to predictive accuracy, the review should evaluate the interpretability, safety, and practical implementation of ML-based dosing systems. Although complex algorithms may identify nonlinear relationships among patient characteristics, their recommendations must be sufficiently understandable for healthcare professionals to assess clinical plausibility and identify potentially unsafe predictions. Explainable artificial

intelligence techniques, feature-importance analysis, uncertainty estimation, and sensitivity analysis may help clarify how individual parameters influence a predicted dose. The review should also examine the potential role of therapeutic drug monitoring in updating dose predictions when measured drug concentrations become available. Integration with electronic health records and clinical decision-support systems may facilitate the use of patient-specific data, although successful implementation requires attention to data interoperability, workflow compatibility, clinician oversight, and institutional validation. Ethical and regulatory considerations, including patient privacy, data security, algorithmic bias, accountability, and the protection of vulnerable pediatric populations, should be considered alongside the potential clinical benefits.

Finally, the information gathered from the literature should be synthesized qualitatively to identify recurring findings, methodological differences, research gaps, and opportunities for future development. The synthesis should compare conventional weight-based dosing, established pharmacometric approaches, and ML-assisted individualized dosing in terms of their underlying principles, data requirements, predictive capabilities, and clinical limitations. Particular emphasis should be placed on the extent to which ML can incorporate multiple patient-specific variables to support more accurate dose selection while maintaining safety and interpretability. The findings should also be used to identify priorities for future research, including multicentre pediatric datasets, external validation, prospective clinical evaluation, standardized reporting practices, and the development of age-appropriate models. Overall, this review methodology provides a framework for understanding the current evidence and future potential of ML-based individualized drug dosing in pediatric pharmacotherapy. Because this methodology is written as a proposed narrative-review framework, the final manuscript should be revised to reflect the databases actually searched, the dates of the searches, the eligibility criteria applied, and the studies genuinely examined. Unless a formal and reproducible screening procedure has been completed, the review should not be described as a systematic review or claim compliance with PRISMA guidelines.

4. Pediatric Pharmacokinetic Variability and Its Importance

4.1 Developmental changes in drug disposition

Drug disposition changes considerably between premature neonates, term neonates, infants, children, and adolescents. These changes influence the dose needed to achieve an effective and safe drug exposure.

- Absorption: Gastric pH, gastric emptying, intestinal motility, and gastrointestinal maturation can affect the absorption of orally administered medicines.
- Distribution: Changes in total body water, extracellular fluid, fat mass, and plasma protein concentrations influence the distribution volume of many drugs.
- Metabolism: Hepatic enzyme activity and drug transporter expression develop at different rates, producing age-dependent differences in drug clearance.
- Excretion: Renal filtration and tubular secretion mature during infancy and childhood, influencing the elimination of renally cleared medications.
- Pharmacodynamic response: The relationship between drug concentration and clinical effect may vary with developmental stage, disease, and receptor sensitivity.

These factors explain why age alone is often insufficient for individualized dosing. Pediatric pharmacometric approaches can incorporate developmental and physiological knowledge to support dose selection and exposure prediction [1,2,6].

4.2 Limitations of conventional dosing approaches

Traditional dosing methods remain essential, but their limitations create opportunities for individualized prediction.

Conventional approach	Principal limitation	Potential contribution of ML
Weight-based dosing	Does not fully represent developmental or organ-function differences	Learns nonlinear relationships between weight and other variables
Body surface area dosing	May not adequately reflect drug-specific clearance	Integrates additional clinical and pharmacological features
Age-band dosing	Broad age categories may overlook individual variability	Uses continuous age and developmental indicators

Fixed maintenance schedules	May not capture changing clearance during illness	Supports reassessment when clinical status changes
Standard TDM adjustment rules	May not incorporate all relevant covariates	Combines measured concentrations with patient-specific information

ML should complement established dosing methods rather than replace validated drug-specific guidance. A predictive model is only useful if its recommendations are reliable for the medication, population, and clinical context in which it is intended to operate.

5. Clinical and Demographic Parameters for Prediction

5.1 Demographic and anthropometric parameters

Important candidate variables include chronological age and, where appropriate, gestational age and postmenstrual age; body weight, height, and body surface area; developmental category; sex-related physiological variables when scientifically justified; and growth trajectory or nutritional status when relevant to the drug.

Weight and age are common baseline predictors, but their relationship with dose requirements may be nonlinear. For example, an algorithm may need to account for developmental maturation and increases in body size rather than assuming that clearance rises proportionally with weight.

5.2 Clinical and laboratory parameters

Clinical parameters can help characterize physiological status and the effects of illness on medication handling. Candidate features include renal function, serum creatinine and appropriately estimated kidney function; hepatic indicators such as bilirubin and relevant enzymes; albumin when relevant; diagnosis and disease severity; hydration and fluid balance; inflammatory markers; and concomitant medicines that may alter drug metabolism or renal clearance.

Laboratory values should be interpreted using pediatric reference ranges and age-appropriate equations. Missing data and measurements taken at different points in the clinical course must be handled carefully.

5.3 Pharmacological and treatment-related parameters

For medicines requiring concentration-guided dose adjustment, pharmacological information may be especially informative. Variables may include drug name, formulation, route, dose history, administration times, treatment duration, measured serum or plasma concentrations, sampling times, previous dose adjustments, observed response, adverse reactions, and pharmacogenomic information when validated and relevant.

Drug concentration measurements are useful only when interpreted alongside dose timing, sampling time, adherence, and the pharmacokinetic properties of the drug.

Table 1. Candidate input variables for individualized pediatric dose prediction

Variable group	Examples	Potential predictive role
Demographic	Age, gestational age, sex	Developmental differences
Anthropometric	Weight, height, body surface area	Body size and distribution
Renal	Creatinine, estimated kidney function	Renal elimination
Hepatic	Bilirubin, relevant enzymes, liver-function indicators	Hepatic metabolism and disease
Clinical	Diagnosis, severity, inflammatory state	Illness-related changes
Medication	Dose history, formulation, route, co-medications	Drug exposure and interactions
Therapeutic monitoring	Drug concentration and sampling time	Estimation of exposure

Outcome	Clinical response, toxicity, adverse events	Assessment of effectiveness and safety
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Note: These are candidate features. Their inclusion must be justified for the individual drug and prediction target.

6. Machine Learning Algorithms for Pediatric Dose Prediction

6.1 Linear and regularized regression

Linear regression can provide a simple baseline for estimating a continuous outcome, such as a dose requirement or drug concentration. Regularized approaches, including ridge and lasso regression, can reduce overfitting when numerous correlated variables are available. These methods are relatively easy to interpret, although nonlinear relationships may require transformations and interaction terms.

6.2 Random forest

Random forest combines predictions from multiple decision trees. It can capture nonlinear relationships and interactions among clinical variables without requiring every relationship to be specified in advance. Potential applications include predicting drug concentrations and identifying patients at risk of subtherapeutic exposure. However, performance outside the training-data range may be unreliable.

6.3 Gradient boosting

Gradient-boosting methods build an ensemble of decision trees sequentially to improve model performance. They can be effective for structured clinical datasets containing demographic, laboratory, and medication variables. Limitations include tuning requirements, overfitting risk, and the need for interpretation methods.

6.4 Support vector regression

Support vector regression estimates continuous outcomes by balancing prediction error against model complexity. With suitable kernels, it can represent nonlinear relationships. It may be useful for smaller curated datasets, although performance can be sensitive to feature scaling and hyperparameter selection.

6.5 Artificial neural networks

Artificial neural networks can model complex relationships across multiple variables and may be useful when sufficiently large and representative datasets are available. They can support longitudinal data integration, but may be difficult to interpret and are vulnerable to bias and information leakage.

6.6 Hybrid pharmacometric and ML models

Hybrid models combine established pharmacokinetic or pharmacodynamic principles with data-driven algorithms. Population pharmacokinetic or physiologically based models can provide mechanistic structure, while ML can characterize complex covariate relationships. This approach is promising but requires comparative evaluation [2,6,7].

Table 2. Comparison of candidate ML approaches

Algorithm	Potential advantage	Main limitation
Regularized regression	Transparent baseline and reduced complexity	Limited flexibility without feature engineering
Random forest	Captures nonlinear relationships and interactions	May extrapolate poorly
Gradient boosting	Flexible for structured data	Requires tuning and careful calibration
Support vector regression	Can model nonlinear patterns in smaller datasets	Sensitive to scaling and parameter selection
Neural networks	Learns complex multidimensional relationships	Requires substantial data and interpretation safeguards
Hybrid pharmacometric–ML	Integrates physiological knowledge with data-driven learning	Greater implementation and validation complexity

No algorithm should be declared the best for all pediatric medications without direct comparative evidence.

7. Proposed Machine Learning Framework

The proposed framework begins with patient-specific data, applies quality control and feature preparation, and generates a prediction that is reviewed by a qualified clinician. The process includes ongoing monitoring to identify changes in clinical status and model performance.

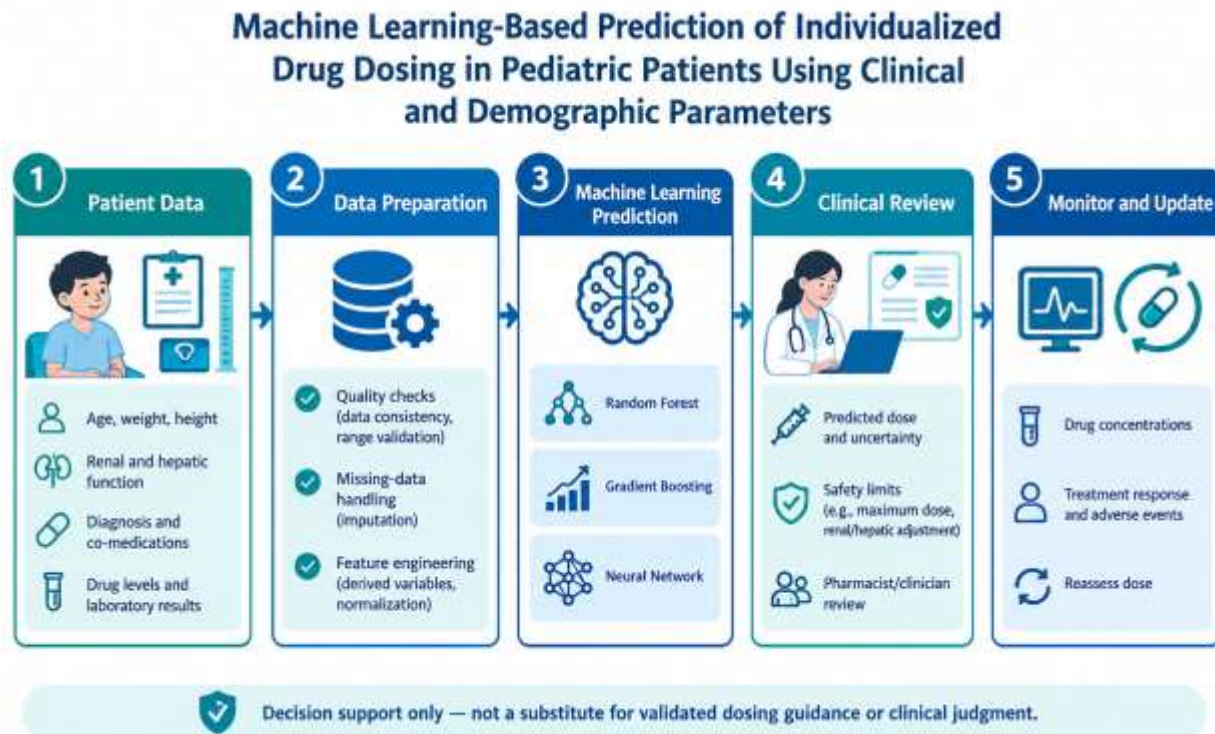


Figure 1. Conceptual workflow for ML-supported individualized pediatric drug dosing. The stages represent a proposed framework, not a tested clinical system.

7.1 Data acquisition and quality control

Data may be obtained from EHRs, pediatric clinical studies, laboratory systems, and therapeutic drug monitoring databases, subject to appropriate authorization. Each record should include clearly defined predictors and an outcome appropriate to the medication. Data quality procedures should identify inconsistent units, implausible values, duplicated records, inaccurate medication histories, and incorrect timestamps. Missing data should be examined to determine whether their absence is related to clinical severity, care processes, or measurement practices.

7.2 Feature engineering

Feature engineering transforms raw measurements into clinically meaningful variables. Examples include age in days for neonates, body surface area derived from height and weight, renal-function categories, cumulative dose, time since the last administration, and dose-normalized concentrations when appropriate. Feature construction must avoid using information unavailable at the moment of prediction.

7.3 Defining the prediction target

A critical design decision is what the model is expected to predict. Possible targets include initial dose requirements, individual drug clearance or concentration at a specified time, probability of attaining a therapeutic target, a recommended adjustment using TDM, or probability of toxicity or treatment failure. These targets are not interchangeable: predicting a concentration does not directly establish the safest dose, and predicting a historical prescription does not identify the optimal regimen.

7.4 Training and validation

Data should be divided into development and evaluation sets using a strategy that reflects the intended deployment setting. Where multiple observations belong to the same patient, patient-level separation is generally necessary to prevent information leakage. Temporal validation can assess later observations, while external validation evaluates transportability to another hospital or population. Hyperparameter tuning should not use the final test set.

7.5 Clinical implementation

A deployed model should function as decision support integrated with prescribing and pharmacy workflows. It should display the prediction target, units, uncertainty, relevant contributing variables, safety warnings, and applicable validated guidance. It should not generate a dose when required information is missing, the patient falls outside the validated population, or the prediction is unreliable.

8. Model Evaluation and Performance Metrics

8.1 Metrics for continuous predictions

For dose or concentration prediction, common metrics include mean absolute error (MAE), the average absolute difference between predicted and observed values; root mean squared error (RMSE), which gives greater weight to larger errors; and mean absolute percentage error (MAPE), which can be misleading when observed values approach zero. Calibration assesses agreement between predicted and observed values, including whether prediction intervals provide appropriate coverage.

8.2 Metrics for classification

When the target is categorical, such as whether exposure falls outside a therapeutic range, relevant measures include sensitivity, specificity, positive predictive value, negative predictive value, and area under the receiver operating characteristic curve. For uncommon but serious adverse events, overall accuracy alone may be misleading.

8.3 Clinical utility and safety

A model should not be considered clinically successful merely because it achieves a low prediction error. Evaluation should determine whether use improves target attainment, reduces adverse drug events, limits unnecessary dose adjustments, or improves other prespecified patient outcomes. Subgroup performance should be examined across relevant age categories and clinical settings.

Table 3. Proposed evaluation framework

Evaluation domain	Suggested assessment	Purpose
Prediction accuracy	MAE, RMSE or suitable classification metrics	Quantify predictive error
Calibration	Calibration plots and suitable statistical measures	Assess agreement between predictions and observations
Generalizability	External and temporal validation	Evaluate performance beyond development data
Clinical benefit	Prospective comparison with usual care	Determine whether predictions improve care
Safety	Dosing-limit violations and adverse outcomes	Identify potential harm
Fairness	Subgroup-specific performance and calibration	Detect systematic differences
Operational reliability	Missing-data handling, workflow fit and monitoring	Assess practical usability

9. Therapeutic Drug Monitoring and Individualized Dose Adjustment

Therapeutic drug monitoring (TDM) involves measuring drug concentrations and interpreting them in relation to dose history, sampling time, pharmacokinetics, and clinical response. It is particularly relevant for selected medications with narrow therapeutic windows or substantial variability in exposure.

ML may enhance TDM by combining drug concentrations with demographic characteristics, laboratory values, treatment history, and other patient-specific variables. A model might estimate individual clearance and forecast the

concentration expected under an alternative regimen. A safe workflow includes collecting the current regimen and appropriately timed concentration; verifying weight, organ function, and clinical status; estimating exposure with a validated method; comparing exposure with a drug-specific target; presenting a potential adjustment for professional review; and reassessing with repeat measurements when indicated.

The exact monitoring schedule and adjustment method must remain drug-specific. An ML model should not assume that every medication has a universal target concentration or that concentration alone adequately represents therapeutic response.

10. Potential Clinical Applications

10.1 Antimicrobial pharmacotherapy

Pediatric antimicrobial dosing may be complicated by developmental differences in renal function, critical illness, fluid shifts, and changing clearance. ML-supported prediction could help estimate exposure or identify patients who may benefit from closer monitoring. Systems must be evaluated against drug-specific pharmacokinetic/pharmacodynamic targets and must not delay necessary therapy or override established recommendations.

10.2 Immunosuppressive therapy

Selected immunosuppressive medications have substantial pharmacokinetic variability and require careful concentration monitoring. Models integrating drug levels, body size, organ function, interacting medicines, and previous doses could support individualized adjustment. Transplant status, disease activity, and treatment-specific risks must also be considered.

10.3 Oncology and supportive care

Pediatric oncology involves medications for which exposure, toxicity, and therapeutic response can vary considerably. ML could help identify patients requiring closer monitoring or support interpretation of multiple clinical and laboratory variables. These applications require rigorous evaluation, established chemotherapy protocols, toxicity criteria, and specialist oversight.

10.4 Analgesics and other commonly used medicines

An individualized model might assist in assessing patient characteristics, organ function, concomitant medications, and adverse-effect risk. Any model must account for medication-specific contraindications, maximum recommended doses, formulation, route, and developmental restrictions.

10.5 Neonatal and infant care

Neonates and young infants present complex dosing challenges because physiological maturation occurs rapidly and available clinical data may be limited. Developmental age and organ function can substantially affect drug handling. Neonatal models require careful assessment of uncertainty and should not be extrapolated beyond validated populations [1,2,6].

11. Proposed Conceptual Model

The proposed framework connects patient characteristics, pharmacological information, prediction algorithms, and clinician-supervised dose adjustment.

1. PATIENT-SPECIFIC INPUT DATA

Age · Weight · Developmental stage · Organ function · Drug history · Laboratory measurements



2. VALIDATED PREDICTION MODEL

Regression · Tree-based learning · Neural networks · Hybrid pharmacometric models



3. INDIVIDUALIZED PREDICTION

Estimated exposure or dose requirement · Uncertainty · Safety screening



4. CLINICAL REVIEW AND DECISION

Prescriber/pharmacist assessment · Validated dosing guidance · Appropriate adjustment



5. MONITORING AND REASSESSMENT

Drug concentrations when indicated · Treatment response · Adverse events · Re-evaluation

Figure 2. Conceptual architecture for integrating ML predictions into pediatric pharmacotherapy. The model supports clinical decision-making and does not independently authorize medication dosing.

The conceptual model is intended to guide future development and evaluation. It does not represent a validated algorithm, and no dose can be calculated from this framework alone.

12. Conclusion

Machine learning offers a promising approach to individualized drug-dose prediction in pediatric patients by integrating demographic, clinical, laboratory, and pharmacological information. Compared with approaches based primarily on age or body weight, appropriately developed ML models may capture complex relationships among developmental maturity, organ function, medication exposure, and treatment response.

However, the potential benefits depend on the quality and representativeness of the underlying data, appropriate model selection, robust validation, interpretability, and integration with established pharmacological knowledge. Particular attention must be given to neonates, infants, children with organ dysfunction, and patients receiving medications with narrow therapeutic windows.

The proposed framework provides a foundation for future research into ML-supported pediatric dosing. Its clinical value must be established through drug-specific development, independent validation, and prospective evaluation of patient outcomes. Ultimately, ML should complement pediatricians, clinical pharmacists, and pharmacologists in making informed, evidence-based dosing decisions while maintaining patient safety and professional accountability.

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