Health Technology and Social Research
https://healthsocres.com

Forecasting Visit Completion in Low Literacy Patients with Telehealth Interface Usability

Haruki Nakano*

Faculty of Pharmaceutical Sciences, Tokyo University of Science, Tokyo, Japan

Corresponding author: haruki.nakano@gmail.com

Abstract

Telehealth has emerged as a cornerstone of modern healthcare delivery, yet its efficacy is often compromised by design barriers that disproportionately affect low-literacy patient populations. This study investigates the relationship between telehealth interface usability and virtual visit completion rates among low-literacy patients using a mixed-methods evaluation framework. We conducted a mixed usability assessment involving one hundred and eighty-six participants categorized as having low health and functional literacy. Usability was measured using quantitative metrics, including task completion time, error rates, and System Usability Scale scores, alongside qualitative thematic analysis of retrospective think-aloud sessions. Predictive modeling, specifically logistic regression and random forest classification, was employed to determine which usability factors most strongly predict successful clinical visit completion. The results demonstrate that cognitive friction, navigation complexity, and icon ambiguity are major inhibitors of visit completion. The predictive model identified task completion time during onboarding and subjective cognitive load as the strongest predictors of overall visit completion. These findings suggest that tailoring telehealth user interfaces to the cognitive needs of low-literacy patients is critical to reducing health disparities and ensuring equitable access to digital medicine.

Keywords: Telehealth Usability; Digital Divide; Low Literacy Patients; Predictive Modeling; Visit Completion

1. Introduction

1.1 The Ascent of Telemedicine and the Digital Divide

The rapid integration of digital technology into the healthcare sector has fundamentally altered the paradigm of clinical consultations. Telemedicine, once a niche service reserved for remote geographic regions, has matured into a mainstream modality of healthcare delivery. This transition was accelerated by global public health crises and the subsequent need to minimize in-person contact. Today, virtual visits are routinely used for chronic disease management, mental health consultations, and primary care follow-ups. Despite the undeniable convenience and efficiency gains associated with digital care, this rapid evolution has exacerbated existing systemic inequalities, giving rise to what is widely conceptualized as the digital divide.

The digital divide refers to the gap between demographics and regions that have access to modern information and communication technology and those that do not. While early research on the digital divide focused primarily on hardware availability and internet connectivity, contemporary scholars distinguish between multiple levels of digital exclusion. The first level concerns physical access to devices and high-speed networks, whereas the second level focuses on digital literacy and the cognitive skills required to navigate complex software systems. In the context of healthcare, this second-level digital divide presents a formidable barrier. Vulnerable populations, particularly individuals with low literacy, often struggle to utilize patient portals, schedule virtual appointments, or initiate video consultations, thereby being effectively excluded from modern healthcare pathways.

1.2 Healthcare Literacy and Cognitive Demands

Health literacy is defined as the degree to which individuals have the capacity to obtain, process, and understand basic health information and services needed to make appropriate health decisions. When digital interfaces become the primary gateway to receiving healthcare, traditional health literacy merges with digital literacy, creating a composite skill set known as digital health literacy. This digital transformation imposes severe cognitive demands on patients. Navigating a telemedicine application requires a sequence of complex tasks, including parsing technical terminology, interpreting abstract visual icons, managing camera and microphone permissions, and executing spatial navigation across nested web pages.

For patients with low functional literacy, these tasks present significant cognitive friction. Cognitive load theory suggests that human working memory has a limited capacity, and when user interface designs are overly complex, they consume excessive extraneous cognitive resources. This reduces the mental bandwidth available for processing actual clinical instructions. Patients with limited literacy skills frequently display distinct behavioral patterns when interacting with digital systems, such as reading web pages word-for-word rather than scanning, misinterpreting metaphors used in iconography, and exhibiting elevated levels of anxiety when encountering system errors. Consequently, interfaces that appear intuitive to developers and tech-savvy clinicians can become insurmountable obstacles for vulnerable patient groups.

1.3 Objectives and Scope

While qualitative usability testing of telehealth applications is common, there is a distinct lack of empirical research that quantitatively links specific interface usability metrics to actual clinical visit completion rates in low-literacy populations. Most existing studies assess usability in a vacuum, focusing on user satisfaction or task performance in simulated scenarios, without tracing the direct impact of these factors on healthcare delivery outcomes. This study aims to address this research gap by establishing a predictive framework that correlates telehealth interface usability with virtual visit completion.

The objective of this research is twofold. First, we implement a comprehensive, mixed-methods usability evaluation designed specifically for low-literacy patients, combining high-resolution quantitative system telemetry with qualitative, retrospective think-aloud protocols. Second, we utilize these multi-dimensional metrics to construct predictive models that identify which specific usability dimensions, such as navigation efficiency, visual layout clarity, and error recovery rate, serve as the strongest determinants of successful telehealth visit completion. By defining these relationships, this study provides actionable, evidence-based guidelines for interface designers and healthcare institutions seeking to make digital medicine accessible to all segments of society.

2. Theoretical Framework and Literature Review

2.1 Technology Acceptance and Usability Models

To understand how low-literacy patients interact with digital health tools, researchers have long relied on established frameworks such as the Technology Acceptance Model [1]. This model posits that the adoption of a technology is primarily determined by two main factors: perceived usefulness and perceived ease of use. While this model has proven highly robust when applied to general populations, its predictive validity decreases when applied to vulnerable users who face structural, educational, and cognitive barriers. For these groups, perceived ease of use is not merely one of several preferences, but a binary gatekeeper. If an interface is too complex, the technology is immediately rejected, rendering perceived usefulness irrelevant.

To capture these nuances, researchers have turned to cognitive load theory, which dictates that mental capacity is limited and must be allocated carefully across different cognitive activities during software interaction [2]. Extraneous cognitive load is generated by the design of the interface itself, such as confusing layouts, poor contrast, and text-heavy instructions. When a telehealth platform generates high extraneous load, low-literacy users exhaust their cognitive reserve on navigation, leaving little to no mental capacity for understanding medical instructions. By integrating usability testing with cognitive load theory, we can better understand how interface friction acts as a direct inhibitor of technology adoption and task completion.

2.2 Usability Challenges in Vulnerable Populations

Empirical literature demonstrates that patients with low literacy, low health literacy, or limited digital exposure experience unique difficulties during software interaction. Previous studies show that low-literacy users frequently struggle with complex hierarchical navigations [3]. These individuals tend to view web pages as static documents rather than interactive environments, meaning they rarely scroll below the fold and often overlook critical interactive elements located on the periphery of the screen.

Furthermore, digital interface designs often fail to account for socio-demographic variations, such as age-related visual decline and cognitive slowing [4]. For instance, abstract visual icons that lack descriptive text labels are highly susceptible to misinterpretation by low-literacy users. A symbol representing a video camera might not register as an interactive link to join a consultation, leading to user confusion and task abandonment. Additionally, error messages on telehealth platforms are frequently written in dense technical jargon. When a system issues a generic error warning regarding camera access or browser compatibility, patients with low literacy lack the troubleshooting vocabulary required to resolve the issue, resulting in immediate frustration and withdrawal from the system.

2.3 Visit Completion as a Quality Metric

In traditional clinical environments, patient adherence is measured by appointment attendance and compliance with treatment regimens. In the digital space, however, telehealth visit completion has emerged as a critical quality and safety metric. Non-completion of virtual visits directly leads to adverse outcomes, including delayed diagnoses, poorly managed chronic conditions, and increased emergency department visits [5].

Despite its clinical significance, telehealth visit completion is frequently hindered by system-level and interface-level barriers. A patient may possess the motivation to consult with a physician, but if they cannot navigate the patient portal to access the video link, the visit is classified as missed. In healthcare research, framing interface usability as a clinical safety metric rather than a mere user preference highlights the ethical necessity of accessible design [6]. Identifying the specific points where users drop out of the digital pathway is the first step toward building a more resilient, equitable telehealth delivery model.

2.4 The Role of Mixed-Methods Evaluation

To comprehensively diagnose usability barriers and predict visit completion, researchers must employ mixed-methods evaluation paradigms. Mixed-methods approaches bridge the gap between telemetry and user cognition [7]. Quantitative usability metrics, such as mouse-click tracking, error frequency, and task completion times, provide objective measures of user performance, enabling statistical modeling and predictive analytics.

However, these numerical values do not explain the underlying cognitive reasons for a user's failure. By integrating qualitative components, such as retrospective think-aloud protocols and semi-structured interviews, researchers can uncover the subjective frustrations, misunderstandings, and cognitive blocks that drive quantitative telemetry trends. For example, while clickstream log data can show that a user repeatedly clicked on the wrong section of a screen, qualitative interview transcripts reveal whether the user did so due to misleading icon design or confusing terminology. Thus, a mixed-methods evaluation yields a richer, highly actionable dataset that can feed directly into predictive algorithmic models.

3. Methodology

3.1 Research Design and Participant Recruitment

This study utilized a cross-sectional, mixed-methods experimental design conducted in a controlled laboratory environment. The protocol received full institutional review board approval prior to commencement, and all participants provided written informed consent. We recruited a cohort of one hundred and eighty-six participants from regional community health centers, public housing developments, and social service agencies.

To ensure the sample accurately represented the target population, we utilized validated screening instruments such as the Rapid Estimate of Adult Literacy in Medicine [8]. Participants scoring below a predetermined threshold, indicating a reading level below the eighth grade, were eligible for inclusion. Additionally, we gathered data on demographic variables, including age, gender, highest educational attainment, and self-reported prior experience with computers and mobile devices.

3.2 The Telehealth Platform Architecture

The telehealth platform evaluated in this study was a standardized, responsive web application configured to simulate a typical clinical patient portal. The system comprised three main functional modules representing the typical patient journey: the onboarding and registration module, the virtual waiting room, and the video consultation interface.

The onboarding module required users to verify their personal details, upload a simulated identification document, and complete a brief pre-visit health questionnaire. The virtual waiting room displayed information regarding the queue status and instructed the user to check their device audio and camera settings. The video consultation interface featured the primary video feed, volume controls, a chat panel, and a prominent end call button. To ensure experimental control, the system was configured to log all user interactions, click events, navigation paths, and time-stamps to a central database with millisecond-level precision.

3.3 Usability Testing and Data Collection

Usability sessions were conducted individually in a dedicated testing suite equipped with high-resolution screen-capture software, an external eye-tracking system, and a testing terminal. Participants were asked to complete five core tasks that replicate a complete telehealth visit: accessing the portal via a login link, completing the pre-visit intake questionnaire, authorizing camera and microphone permissions, joining the virtual waiting room, and successfully establishing a video call with a remote researcher playing the role of the clinician.

During the sessions, quantitative telemetry software recorded clickstream data, including task completion time, total clicks per task, and error rates, which were defined as clicking non-interactive elements or navigating away from the target path. Following task completion, participants completed a simplified, orally administered version of the standardized System Usability Scale [9]. This instrument has been validated for use in diverse populations and yields a score ranging from zero to one hundred, reflecting overall perceived system usability.

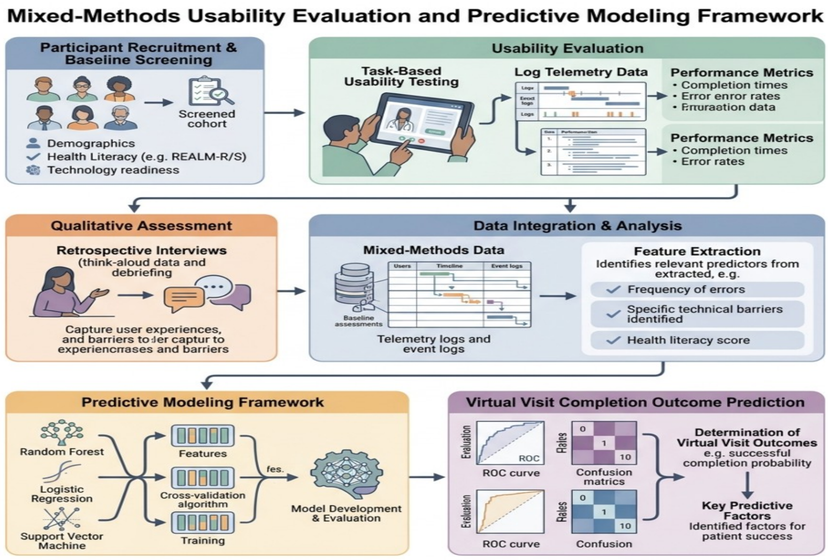

Figure 1: Comprehensive Workflow of the Mixed

3.4 Qualitative Assessment and Think-Aloud Protocols

To capture the qualitative dimensions of user interaction without artificially inflating cognitive load during task execution, we implemented a retrospective think-aloud protocol. During the testing session, participants performed tasks in silence to ensure natural behavior and realistic cognitive load. Immediately following the completion of the final task, the researcher played back a video recording of the participant's screen interaction.

Using this recording as a visual prompt, the participant was asked to explain their thought processes, visual search strategies, and the reasons behind specific errors or delays. These verbalizations were audio-recorded, transcribed verbatim, and subjected to inductive thematic analysis. Coding was performed by two independent researchers, and discrepancies were resolved through discussion to achieve a high level of inter-rater reliability, ensuring the systematic capture of user frustration, confusion, and interface satisfaction.

4. Quantitative Analysis and Predictive Modeling

4.1 Statistical Modeling of Completion Rates

The primary objective of the quantitative analysis was to model the probability of successful virtual visit completion as a function of the collected usability metrics. Visit completion was defined as a binary outcome variable, where a value of one represented successful completion of all five task phases without investigator intervention, and a value of zero represented task abandonment or the necessity of external intervention due to complete user disorientation.

Predictor variables entered into the model included average task completion time, cumulative error rate, icon misinterpretation rate, and adapted System Usability Scale score. We used logistic regression to determine the individual predictive power and odds ratios of these usability metrics. Concurrently, a random forest classification algorithm was trained on the dataset to model complex interactions and non-linear associations among the predictors. This dual-modeling strategy allowed for robust performance validation and the generation of feature importance rankings.

4.2 Handling Missing Data and Multicollinearity

Prior to model training, the dataset underwent comprehensive preprocessing. Missing values, which occurred primarily in eye-tracking metrics due to occasional participant movement outside the tracker sensor field, were handled using multiple imputation by chained equations. This method preserves statistical power and minimizes bias compared to complete-case analysis.

A critical step in preparing the logistic regression model was assessing and mitigating multicollinearity. Highly correlated features, such as total task completion time and cumulative error rate, can destabilize regression coefficients, making it difficult to isolate individual predictor impacts. We addressed multicollinearity issues using variance inflation factor thresholding [10]. Variables exhibiting a variance inflation factor greater than five were sequentially removed or combined into composite scores. Specifically, task completion time and error rates were standardized and combined into an overall task performance index, which resolved the multicollinearity issues.

4.3 Evaluation Metrics for Predictive Algorithms

To determine the utility and accuracy of our predictive models, we utilized several standard classification evaluation metrics. The primary performance indicator was the area under the receiver operating characteristic curve, which evaluates the model's ability to distinguish between completed and abandoned visits across all classification thresholds [11].

Additionally, we calculated classification accuracy, sensitivity, and specificity. Sensitivity, in this context, measures the model's accuracy in predicting successful visit completion, while specificity evaluates the model's ability to correctly identify patients at high risk of abandonment. To prevent overfitting and ensure the generalizability of our predictive findings, we implemented a five-fold cross-validation scheme. Under this protocol, the dataset was randomly partitioned into five subsets; the models were iteratively trained on four subsets and validated on the remaining subset, with the final performance metrics averaged across all five iterations.

5. Results and Usability Findings

5.1 Demographic and Baseline Characteristics

The demographic analysis of the cohort confirmed that the recruitment strategies were successful in targeting individuals with low literacy and limited technology exposure. The average age of the participants was fifty-four years, with a standard deviation of twelve years. Over sixty percent of the sample identified as female, and more than seventy percent reported a household income below the federal poverty line.

Importantly, seventy-four percent of participants reported using a smartphone as their primary computing device, while only twenty-six percent had regular access to a desktop or laptop computer. Literacy assessment scores indicated that forty-five percent of the sample possessed reading skills equivalent to a third-to-fifth-grade level, while fifty-five percent fell into the sixth-to-eighth-grade equivalent range. This baseline characterization highlights the vulnerability of the study population to digital barriers.

Table 1: Demographic and Baseline Characteristics of Study Participants

Demographic Variable	Category	Frequency	Percentage
Age	18 to 39	28	15.1
Age	40 to 59	82	44.1
Age	60 and older	76	40.8
Gender	Female	115	61.8
Gender	Male	71	38.2
Device Use	Smartphone	138	74.2
Device Use	Desktop or Laptop	48	25.8

Demographic Variable	Category	Frequency	Percentage
Reading Grade Level	3rd to 5th Grade	84	45.2
Reading Grade Level	6th to 8th Grade	102	54.8

5.2 Usability Metrics and Performance Data

The quantitative usability testing revealed substantial performance variations across the different phases of the simulated telehealth visit. Out of the one hundred and eighty-six participants, only ninety-eight successfully completed all five tasks without prompting or intervention, yielding an overall completion rate of fifty-two point seven percent. Systematic error patterns often reveal structural layout deficiencies [12].

The highest error rates and longest task completion times were observed during the pre-visit intake questionnaire and the device permission authorization phase. On average, participants spent over three hundred seconds attempting to complete the intake questionnaire, with a mean error rate of four point two errors per participant. The System Usability Scale scores reflected these difficulties, with the cohort yielding a mean score of fifty-four point eight out of one hundred, well below the benchmark of sixty-eight that typically denotes acceptable usability.

Table 2: Usability and Task Performance Summary

Task Description	Average Time in Seconds	Mean Error Count	Task Completion Rate
Portal Login	120.4	1.8	78.5
Intake Questionnaire	312.6	4.2	58.1
Permission Granting	185.1	2.9	62.4
Waiting Room	95.3	0.9	88.2
Joining Video Call	145.8	2.1	68.8

5.3 Predictive Modeling Outcomes

The logistic regression and random forest models demonstrated high accuracy in predicting visit completion based on usability telemetry. The logistic regression model achieved an overall accuracy of seventy-eight point five percent, with a sensitivity of eighty-one point two percent and a specificity of seventy-five point four percent. The area under the receiver operating characteristic curve was zero point eighty-four, indicating strong predictive discrimination.

The random forest classifier performed slightly better, yielding an accuracy of eighty-one point two percent and an area under the curve of zero point eighty-seven. Feature importance analysis from the random forest model revealed that onboarding task completion time and permission-granting error rates were the most significant predictors of visit completion. Perceived usability, represented by the adapted System Usability Scale score, was also a strong predictor, while age and device type had lower predictive value in the final model, indicating that usability factors outweigh basic demographic characteristics in determining telehealth success.

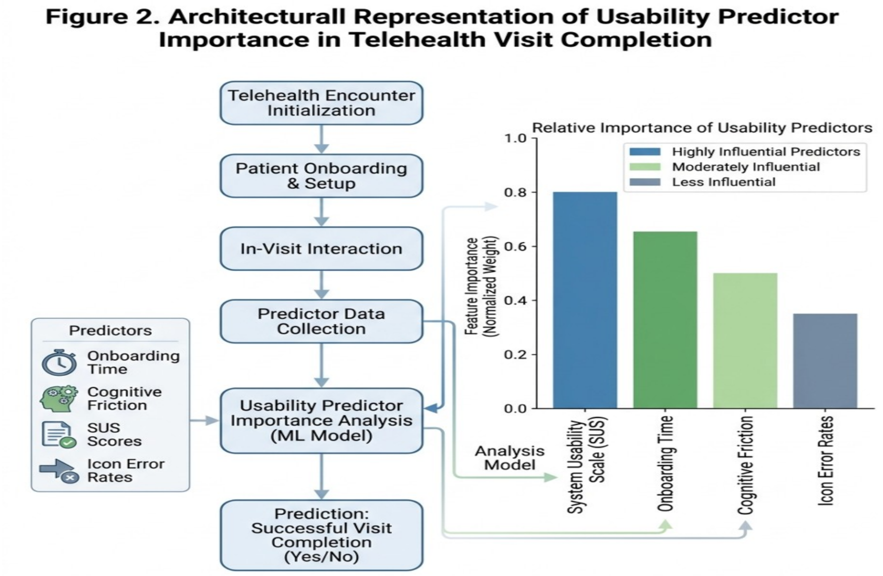

Figure 2: Detailed Architectural Representation of Usability Predictor Importance in Telehealth Visit Completion

5.4 Qualitative Themes and Cognitive Obstacles

Thematic analysis of the retrospective think-aloud transcripts identified four primary cognitive obstacles that directly contributed to task abandonment. The first theme, metaphorical confusion, occurred when participants misidentified abstract icons. For instance, many interpreted a gear icon as a flower or a loading symbol rather than settings, preventing them from resolving camera configuration issues.

The second theme, text density overload, was characterized by feelings of anxiety and fatigue when encountering dense screens of text. Many participants reported that they stopped reading instructions entirely when more than three sentences were presented on a single page. The third theme was error message helplessness. When browser error pop-ups appeared, participants felt they had made a permanent mistake and frequently chose to close the app rather than try to fix it. Finally, the fourth theme highlighted visual hierarchy failure, where participants overlooked action buttons, such as a green button to enter the video call, because the interface was cluttered with secondary visual elements.

6. Discussion and Practical Implications

6.1 Synthesizing Usability and Visit Completion

The results of this study establish a clear, direct relationship between interface usability and successful virtual visit completion. Our predictive model demonstrates that telehealth completion is not merely a matter of patient motivation or internet connection quality; rather, it is highly dependent on the design of the user interface. When vulnerable patients encounter high levels of cognitive friction, they are highly likely to abandon the digital visit, which directly links low interface usability to marginalized healthcare access [13].

By identifying specific points of failure, such as device permission granting and onboarding questionnaire completion, this study shows where system developers should focus their attention. Reducing task completion times and error rates during these early phases can significantly lower cognitive fatigue, thereby increasing the likelihood that patients will successfully reach and complete the clinical portion of their virtual visit. Usability must therefore be recognized as a critical clinical variable that directly impacts healthcare access for vulnerable populations.

6.2 Design Guidelines for Inclusive Telehealth

To mitigate these usability barriers, telemedicine interfaces must be designed to accommodate the cognitive and literacy needs of all patients. We propose several actionable design guidelines based on our empirical and qualitative findings. First, text-heavy instructions should be replaced with simple language, short bullet points, and, where possible, video or audio guides. Visual elements must be highly structured, using a linear, step-by-step layout rather than a dense dashboard.

Second, iconography must be accompanied by explicit text labels. Relying solely on abstract icons introduces significant risk of misinterpretation; combining a simple icon with plain language ensures clarity. Third, the process for granting device permissions (camera and microphone) must be simplified. Standard browser prompt pop-ups are often confusing; instead, platforms should use native, in-app permission wizards with clear visual and audio prompts. Finally, error messages must be rewritten to avoid technical jargon, focusing instead on simple, step-by-step instructions for recovery.

6.3 Study Limitations and Future Research

While this study provides valuable insights, several limitations must be acknowledged. First, the usability evaluations were conducted in a controlled laboratory environment. While this setup allowed for precise eye-tracking and interaction logging, it may not fully capture the distractions, environmental noise, and connectivity fluctuations that occur in a patient's home. Second, our study focused on a single, representative web-based patient portal. Different system designs, such as native mobile applications or SMS-based telehealth links, may present different usability profiles.

Future research should focus on validating these predictive models in real-world home settings, using longitudinal clinical trials to trace the long-term impact of accessible design on healthcare outcomes. Additionally, researchers should explore the potential of emerging technologies, such as voice-user interfaces and artificial intelligence-driven navigation assistants, to further simplify the telehealth onboarding process for low-literacy patients. By continuing to prioritize usability and digital inclusion, the medical informatics community can help ensure that the benefits of telemedicine are shared equitably by all.

References

1. Kuepfer, L.; Niederalt, C.; Wendl, T.; Schlender, J.F.; Willmann, S.; Lippert, J.; Block, M.; Eissing, T.; Teutonico, D. Applied Concepts in PBPK Modeling: How to Build a PBPK/PD Model. CPT Pharmacomet. Syst. Pharmacol. 2016, 5, 516–531.

2. Czuba, L.C.; Malhotra, K.; Enthoven, L.; Fay, E.E.; Moreni, S.L.; Mao, J.; Shi, Y.; Huang, W.; Totah, R.A.; Isoherranen, N.; et al. CYP2D6 Activity Is Correlated with Changes in Plasma Concentrations of Taurocholic Acid during Pregnancy and Postpartum in CYP2D6 Extensive Metabolizers. Drug Metab. Dispos. 2023, 51, 1474–1482.

3. Lou, J.Q.; Huo, B.N.; Yang, Y.; Wang, S.F.; Zhang, L.D.; Jia, Y.T.; Song, L. Physiologically Based Pharmacokinetic Modeling and Dose Optimization of Linezolid in Pediatric Patients With Renal Impairment. Drug Des. Devel. Ther. 2025, 19, 8427–8440.

4. Darwich, A.S.; Ogungbenro, K.; Vinks, A.A.; Powell, J.R.; Reny, J.L.; Marsousi, N.; Daali, Y.; Fairman, D.; Cook, J.; Lesko, L.J.; et al. Why has model-informed precision dosing not yet become common clinical reality? lessons from the past and a roadmap for the future. Clin. Pharmacol. Ther. 2017, 101, 646–656.

5. Tonka, J.; Schyns, M. The Digital Twin Concept: A Definition Attempt; University of Liège (ULiège): Liège, Belgium, 2021.

6. Tsantili-Kakoulidou, A.; Demopoulos, V.J. Drug-like Properties and Fraction Lipophilicity Index as a combined metric. ADMET DMPK 2021, 9, 177–190.

7. Silva, A.; Mourão, J.; Vale, N. Molecular Precision Medicine: Application of Physiologically Based Pharmacokinetic Modeling to Predict Drug-Drug Interactions Between Lidocaine and Rocuronium/Propofol/Paracetamol. Int. J. Mol. Sci. 2025, 26, 1506.

8. Curry, L.; Alrubia, S.; Bois, F.Y.; Clayton, R.; El-Khateeb, E.; Johnson, T.N.; Faisal, M.; Neuhoff, S.; Wragg, K.; Rostami-

Hodjegan, A. A guide to developing population files for physiologically-based pharmacokinetic modeling in the Simcyp Simulator. CPT Pharmacomet. Syst. Pharmacol. 2024, 13, 1429–1447.

9. Saeedi, M.; Eslamifar, M.; Khezri, K.; Dizaj, S.M. Applications of nanotechnology in drug delivery to the central nervous system. Biomed. Pharmacother. 2019, 111, 666–675.

10. Fendt, R.; Hofmann, U.; Schneider, A.R.P.; Schaeffeler, E.; Burghaus, R.; Yilmaz, A.; Blank, L.M.; Kerb, R.; Lippert, J.; Schlender, J.F.; et al. Data-driven personalization of a physiologically based pharmacokinetic model for caffeine: A systematic assessment. CPT Pharmacomet. Syst. Pharmacol. 2021, 10, 782–793.

11. Barr, S.; Hill, E.W.; Bayat, A. Functional Biocompatibility Testing of Silicone Breast Implants and a Novel Classification System Based on Surface Roughness. J. Mech. Behav. Biomed. Mater. 2017, 75, 75–81.

12. Lehmann, E.L. The Fisher, Neyman-Pearson Theories of Testing Hypotheses: One Theory or Two? J. Am. Stat. Assoc. 1993, 88, 1242–1249.

13. Radke, C.; Horn, D.; Lanckohr, C.; Ellger, B.; Meyer, M.; Eissing, T.; Hempel, G. Development of a Physiologically Based Pharmacokinetic Modelling Approach to Predict the Pharmacokinetics of Vancomycin in Critically Ill Septic Patients. Clin. Pharmacokinet. 2017, 56, 759–779.