



BAYESIAN MODELING OF FLUID FLOW EFFECTS IN DRUG-RELEASING ORTHOPEDIC IMPLANTS

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Abstract

Drug-releasing orthopedic implants are increasingly used to enhance localized therapy and reduce post-operative infections; however, drug transport at the implant-tissue interface is strongly influenced by physiological fluid flow and patient-specific variability. Conventional deterministic models are widely used to describe drug transport mechanisms and provide mechanistic insight under fixed and/or initial conditions; however, they are limited in their ability to quantify physiological and patient-specific uncertainties, resulting in reduced predictive reliability of therapeutic outcomes. This research study proposes a Bayesian Belief Network (BBN) framework to probabilistically model fluid flow effects in drug-releasing orthopedic implants. Nine root variables, five intermediate variables, and one outcome variable (therapeutic efficacy) were identified and structured within Bayesian directed acyclic graph. Prior and conditional probabilities were estimated using a combination of published literature, expert knowledge, and clinical data. Four types of Bayesian reasonings were carried out; namely diagnostic reasoning, patient-specific reasoning, fluid dynamic reasoning and implant design reasoning to identify critical determinants of drug-releasing orthopedic implant's therapeutic performance. Bayesian causal inference predicted a 58.6% probability of effective therapeutic efficacy. The analysis revealed that high fluid velocity reduces drug retention time, while coating thickness and implant material significantly influence release kinetics. Patient-specific factors, including joint type, bone porosity, and inflammation level, were also found to exert substantial effects on drug diffusion, infection risk, and implant failure probability. The proposed BBN framework provides a robust decision-support tool that captures physiological and implants design uncertainties previously under-quantified in deterministic models. By quantifying uncertainty through probabilistic representations rather than single-point estimates, this approach enables patient-specific optimization of implant design and drug-release strategies, thereby improving predictive accuracy, reducing clinical risk, and advancing personalized orthopedic implant development.

1.0 INTRODUCTION

Orthopedic implants like joint prosthetics and bone plates are vital for restoring the mobility and functions for patient who has issues with degenerative disorders or skeletal injuries. Recently, attentions have been drawn to orthopedic implants that have ability to release drugs locally and subsequently improve healing and prevent infections. However, the interactions at the implants-tissues interface due to implants materials, fluid dynamics and bone plates interactions affect the dynamics of the implants environment [1]. There is a scarcity of modelling and conventional fluid mechanics literature that capture the uncertainties between

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biological variability, materials flaws or patient-specific characteristics in a drug releasing orthopedic implant system. Bayesian Belief Network (BBN) is a probabilistic modelling technique that combines expert opinions and empirical data to model the uncertainty inherent in any system. Considering the stochastic nature of fluid flows and the dynamics of drugs release, BBN offer a framework for prediction of system outcomes dynamically [2], [3].

Conversely, there are past researches that have reported the modeling and simulation of drug-releasing implant that offered local provisions of antibiotics, anti-inflammatory drugs and bone-growth hormones for bone tissue healing [4], [5]. These implants also have the capability to reduce the systemic pharmacological side effects while maximizing localized healing. King [6] used a hybrid of analytical and numerical modeling approaches to study drug release from orthopedic implants (OIs). The models incorporated diffusion and dissolution processes to simulate the release of antibiotics and their effects on bacterial growth. Model results showed that variable porosity, device geometry and fluid flow considerations impact drug release rates while antibiotic solubility can lead to treatment failure. Jain et al. [7] research presented a mathematical model using the eigenfunction expansion method to analyze drug dissolution and diffusion from a cylindrical drug-filled device surrounded by a porous encapsulant. The model successfully predicts drug release profile with initial drug concentration playing a crucial role in determining whether the system is diffusion-limited or dissolution-limited and that Drug release is influenced by encapsulant properties, with thicker or lower-permeability encapsulants slowing down drug diffusion. The model results also showed encapsulant thickness, porosity, and drug concentration as key parameters for optimizing drug delivery systems.

Furthermore, Adeleye et al. [8] formulated a set of coupled partial differential equations to model the effects of interface layer thickness ratio, porosity, and effective diffusion coefficient on drug concentration profiles in single- and double-layer orthopedic implant coatings. Model results showed that increasing the interface layer thickness ratio say from 0.2 to 0.8 results in a significant decrease in drug concentration profiles across both single and double layers while porosity and diffusion coefficient parameters exhibited a dominant influence on drug release rates.

In the same vein, McGinty & Pontrelli [9] presented a generalized two-layer mathematical model that simultaneously accounts for drug diffusion, dissolution, and solubility within the polymer coating of a drug delivery devices while modeling diffusion, convection, and different forms of drug binding within biological tissue. The model results showed that factors such as drug solubility, dissolution rate, and the binding mechanism significantly affect drug release profiles. However, there are problems of attaining consistent and prolonged drug release due to the complicated interactions at the implant-tissue interface [10]. Fluid flow at the implant-tissue interface is important in defining drug release pattern. Meanwhile, model like finite element analysis (FEA) are restrained by the deterministic nature (namely initial conditions) [11]. The effects of external factors fluid flow at the implants-tissue also make (like synovial fluid mobility and bone porosity fluctuations) prediction of effective therapeutic or risk of infection difficult. BBN can resolve these difficulties as it has been successfully used to model uncertainty and prediction of outcomes [12].

Deterministic orthopedic drug-release models developed in previous studies provide valuable mechanistic insight but do not capture the variability inherent in real implant-tissue environments. King [6], for instance, simulated drug-filled implants using fixed geometric and fluid-flow parameters, thereby neglecting patient-specific variability in bone porosity, tissue flow, and coating behavior. Similarly, Jain et al. [7] analyzed dissolution and diffusion under static conditions that excluded convective flow and biological heterogeneity. Adeleye et al. [8] also assumed constant coating thickness, porosity, and diffusion parameters, ignoring fabrication tolerances and biological fluctuations that occur in practice. Even the comprehensive PDE model of McGinty & Pontrelli [9] treated all transport and binding parameters as fixed values fitted to averaged data, thus masking inter-patient differences. Collectively, these deterministic approaches cannot quantify uncertainty or predict how drug-release outcomes vary across individuals or physiological conditions. This creates a clear research gap in modeling therapeutic efficacy and risk of infection under realistic variability. The Bayesian Belief Network (BBN) approach adopted in this study fills this gap by treating key implant, biological, and fluid-dynamic factors as probabilistic variables and propagating their uncertainties to generate personalized predictions of therapeutic effectiveness.



Some past researches have reported the use of BBN in health-care system and biomedical engineering. McLachlan et al. [13] reported the application of BBN to access a range of medical diseases. BBN was used to model four illnesses that account for about two-third of overall healthcare-related research. These illnesses are heart ailment, cancer, psychological disorders and lung diseases. In the same vein, Collins and Fenton [14] also used BBN to model the prediction of the early detection of endometriosis. Parent nodes (variables) considered in the research includes family history, past surgeries end symptoms. The BBN model developed can also update prediction capability whenever new information is available. The BBN model also identifies critical variables through diagnostic inference for endometriosis management.

Furthermore, Semakula et al. [15] applied BBN to model the prediction and ranking of malaria risk factors amongst children within the age bracket of 1-5 yrs in a refugee camp in Ugandan. BBN variables are based on demographic, socioeconomics and environmental characteristics were obtained from the Ugandan malaria indicator survey between 2018 and 2019. The BBN model prediction accuracy was 91.11% while the diagnostic reasoning identified child age, house materials, ITN use, toilet facilities and access of water as critical variables (factors) of interest. These critical variables are indicators of malaria interventions where there are limited funds. In the same vein, Nordmann and Berdeaux [16] also applied BBN for the prediction of the peaks above 18mmHg of overnight intraocular pressure (IOP) of glaucoma patients. The result of the research study shows that BBN has been successfully used to predict the glaucoma therapeutic outcome of IOP peaks.

Local drug release through the use of orthopedic implants have impediments due to the unpredictable fluid flow at the implants-tissue interface thereby affecting the therapeutic outcome which is affected by drug distribution, drug diffusion rate and patient-specific factors. Past research study have applied deterministic modeling technique to evaluate the therapeutic outcomes of drug releasing effect of orthopedic implants but this technique hardly considers the significance of variability and uncertainty of material property, implant geometry and patient-specific factors. There are scarce or no adequate prediction methods to evaluate this uncertainty level of the therapeutic outcome, risk of infection and implant failure due to flow effect of

drug releasing orthopedic implant [17]. The prediction of therapeutic outcome of fluid flow effect in drug releasing orthopedic implant using BBN is the subject of this research study.

2.0 MATERIALS AND METHODS

2.1 Developing Bayesian Belief Network (BBN) Framework

The first step in this research study involved the development of a Bayesian Belief Network (BBN) framework tailored to model fluid flow effects in drug-releasing orthopedic implants. The BBN was constructed using a directed acyclic graph (DAG) where nodes represented variables related to fluid flow effects in drug-releasing orthopedic implants. Each node was defined by its conditional probability distributions, which were derived from existing literature and empirical data. The relationships between nodes were established based on expert knowledge and prior studies, ensuring that the model accurately reflects the underlying biological and mechanical processes influencing fluid flow around the implant. The BBN was implemented using software tool namely Netica, which facilitate the graphical representation and computational analysis of probabilistic models. Bayesian Belief Network reasoning was performed to identify key variables that significantly influence the outcomes, thereby refining the focus of subsequent analyses.

2.2 Identifying Bayesian Variables for Drug-Releasing Orthopedic Implants

To enhance the BBN's applicability, Bayesian variables were obtained from survey of literature [4]-[11], [14], [15], [18], experts' opinions and clinical data from orthopedic hospitals in Southwest Nigeria. These data were then converted into a format compatible with the BBN framework. As a result, Table 1 presented the list of Bayesian variables that influence the fluid flow effects in drug-releasing orthopedic implants. These Bayesian variables are the root factors (referred to as parent nodes) that affects the final outcome (referred to as the child node) in the Bayesian Belief Network (BBN) framework.

It should be noted the final outcome of this research study is therapeutic efficacy, which is the effectiveness of the drug in achieving desired therapeutic outcomes, which can vary amongst patients.



2.3 Estimating Prior Probabilities of Bayesian Variables for Drug-Releasing Orthopedic Implants

Estimating prior probabilities of Bayesian variables is a crucial step in developing a robust Bayesian Belief Network (BBN) for drug-releasing orthopedic implants. Prior probabilities represent the initial beliefs about the likelihood of various outcomes before observing new data. For the purpose of this research study, Bayesian variables have been categorized under patient-specific variables, fluid dynamics variables and implant design variables. For patient-specific variables, namely bone porosity, inflammation level, and joint type, prior probabilities were estimated from expert opinions and knowledge and historical clinical data. For the fluid dynamics variables namely fluid velocity, implant porosity and viscosity of fluid and the implant design variables namely coating techniques, material type, and drug concentration in coatings, prior probabilities were estimated through expert opinions and scientific literature reviews [4]-[11], [14], [15], [18].

Experts' opinions and knowledge were used to develop the conditional probability table (CPT) for the child node and intermediate nodes. Majority of the experts employed for this research study were drawn from academic staff of Departments of Biomedical Engineering and Pharmacology of University; and medical practitioners from orthopedic hospitals with each of them having at least 5-10 years experience on the job.

3.0 RESULTS AND DISCUSSION

3.1 Results

3.1.1 Evaluation of fluid flow effects in drug-releasing orthopedic implants

Bayesian causal inference was used to evaluate the fluid flow effects in drug-releasing orthopedic implants. Nine root causal factors influencing the effects of fluid flow in drug-releasing orthopedic implants were identified and modeled alongside five intermediate causal factors. The Bayesian influenced model is shown in Figure 1. From Figure 1 below, the root causal factors contributing to effective or ineffective therapeutic efficacy of fluid flow effects in drug releasing orthopedic implants are fluid velocity, joint type, implant porosity, viscosity of fluid, material type, coating techniques, drug concentration in coating, bone porosity and inflammation level while the intermediate causal factors are flow regime, drug diffusion rate, drug release rate, implant failure risk and risk of infections. The final outcome otherwise known as the child node is the therapeutic efficacy of the orthopedic implant.

The child node has two states namely effective and ineffective (Figure 1) while the intermediate nodes and the root nodes also have two states each (Figure 1 and Table 1). From Figure 1, the causal inference showed the probability of effective therapeutic efficacy was 58.6% while the probability that it is ineffective was 41.4%.

Table 1: States of parent nodes and their corresponding prior probabilities

S/N	Parent Nodes	Symbols	Parent Nodes States	Prior Probabilities (%)
1	Fluid Velocity	FV	➤ High Velocity ➤ Low Velocity	0.2 0.8
2	Joint Type	JT	➤ Fixed Joint ➤ Mobile Joint	0.3 0.7
3	Implant Porosity	IP	➤ High Porosity ➤ Low Porosity	0.3 0.7
4	Viscosity of Fluid	VoF	➤ High Viscosity ➤ Low Viscosity	0.7 0.3
5	Material Type	MT	➤ Polymer ➤ Metallic	0.65 0.35
6	Coating Techniques	CT	➤ Thick Coating ➤ Thin Coating	0.4 0.6
7	Drug Concentration in Coating	DCiC	➤ High Concentration ➤ Low Concentration	0.75 0.25
8	Bone Porosity	BP	➤ High Bone Porosity ➤ Low Bone Porosity	0.3 0.7
9	Inflammation Level	IL	➤ High Inflammation ➤ Low Inflammation	0.15 0.85



3.1.2 Bayesian belief network reasoning

Bayesian Belief Networks (BBNs) have been successfully utilized to model the complex interactions involved in fluid flow effects in drug-releasing orthopedic implants. The Bayesian reasoning considered in this research study are diagnostic inference (Figure 2) and the effects of patient-specific variables (Figure 3), fluid dynamics variables (Figure 4) and implant design variables (Figure 5) in drug-releasing orthopedic implants respectively. The reasoning inferences determined the posterior probability of therapeutic efficacy of the drug-releasing orthopedic implants and consequently, the critical variables were evaluated when compared with the prior probability of variables. Figures 2, 3, 4 and 5 showed the posterior probability for diagnostic inference, patient specific variable inference, fluid dynamics variable inference and implant design variable inference respectively. Comparing the posterior probability of the intermediate variables and root variables from the diagnostic inference reasoning as shown in Figure 2 with the prior probability of the intermediate variables and root variables when therapeutic efficacy is effective was observed; revealed profound and marginal changes in their values respectively.

Considering the intermediate nodes, the probability of implant failure risk is high (dropped by 48.4%), that of risk of infection is high also dropped by 17.3%. In the same vein, the probability of drug diffusion rate is fast diffusion and drug release rate is high release also dropped by 12.3% and 12.8% respectively while the probability of flow regime is laminar increased by 2.7%. Conversely, marginal changes were observed when the posterior probabilities of the root variables were compared with the corresponding prior probability. Marginal changes observed are namely the probability of viscosity of fluid is low viscosity (decreased by 3.7%), the probability of material type is polymer (decreased by 2.7%), the probability of coating techniques is thin coatings (decreased by 2.0%) and the probability of drug concentration in coating is high concentration (decreased by 1.2%) respectively. While marginal increase in values were observed for the probability of fluid velocity is low velocity (increased by 2.1%), the probability of implant porosity is low porosity (increased by 1.4%) and the probability of inflammation level is low inflammation and the probability of bone porosity is low bone porosity increased by 0.7% and 0.4% respectively.

Furthermore, Figures 3, 4 and 5 depicted the effects of patient-specific variables, fluid dynamics variables and implant design variables on the final outcomes of the drug-releasing orthopedic implants system when they were independently observed. From Figure 3, there were marginal changes in posterior probability of therapeutic efficacy is effective (increased by 0.52%), posterior probability of risk of infection is high (increased by 1.9%) while posterior probability of implant failure risk is high dropped by 2.96% when the patient specific variables namely bone porosity is low bone porosity, inflammation level is low inflammation and joint type is mobile joint were observed. In the same vein, Figure 4 also showed marginal changes in the posterior probability of therapeutic efficacy is effective (increased by 0.52%) while both posterior probability of risk of infection is high (dropped by 0.549%) and posterior probability of implant failure risk is high also dropped by 0.63% when fluid dynamics variables namely fluid velocity is low velocity, implant porosity is low porosity and viscosity of fluid is low viscosity were observed. Conversely, Figure 5 showed the effects of implant design variables reasoning when they were observed. The posterior probability of effective therapeutic efficacy (increased by 0.52%) while the posterior probability of risk of infection is high (increased by 37.1%) and posterior probability of implant failure risk is high dropped by 23.3%. This is a significant change observed for this reasoning and this revealed that the implant design variables are critical to implant failure risk and risk of infection.

Figures 6 and 7 showed the effects of drug diffusion rate is fast diffusion and drug release rate is high release rate on the final outcomes (therapeutic efficacy is effective, risk of infection is high and implant failure risk is high) when they were observed independently. Profound changes were observed in the two scenarios namely; when drug diffusion rate is fast diffusion, the posterior probability of therapeutic efficacy is effective (decreased by 12.5%) and also the posterior probability of risk of infection is high decreased by 37.1% while posterior probability of implant failure risk is high increased by 71.8% and when drug release rate is high release rate, the posterior probability of therapeutic efficacy is effective (decreased by 12.8%) and also the posterior probability of risk of infection is high decreased by 45.3% while posterior probability of implant failure risk is high increased by 73.1%.



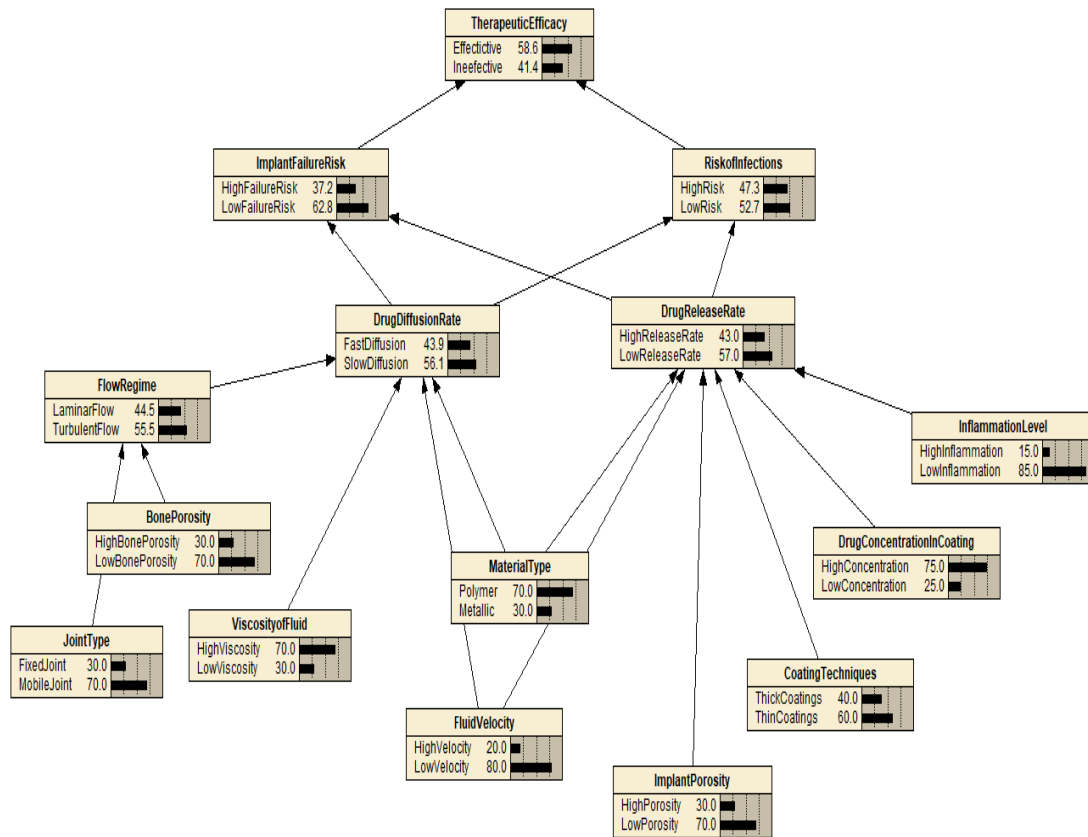


Figure 1: Bayesian causal influence diagram for evaluating fluid flow effects in drug-releasing orthopedic implants

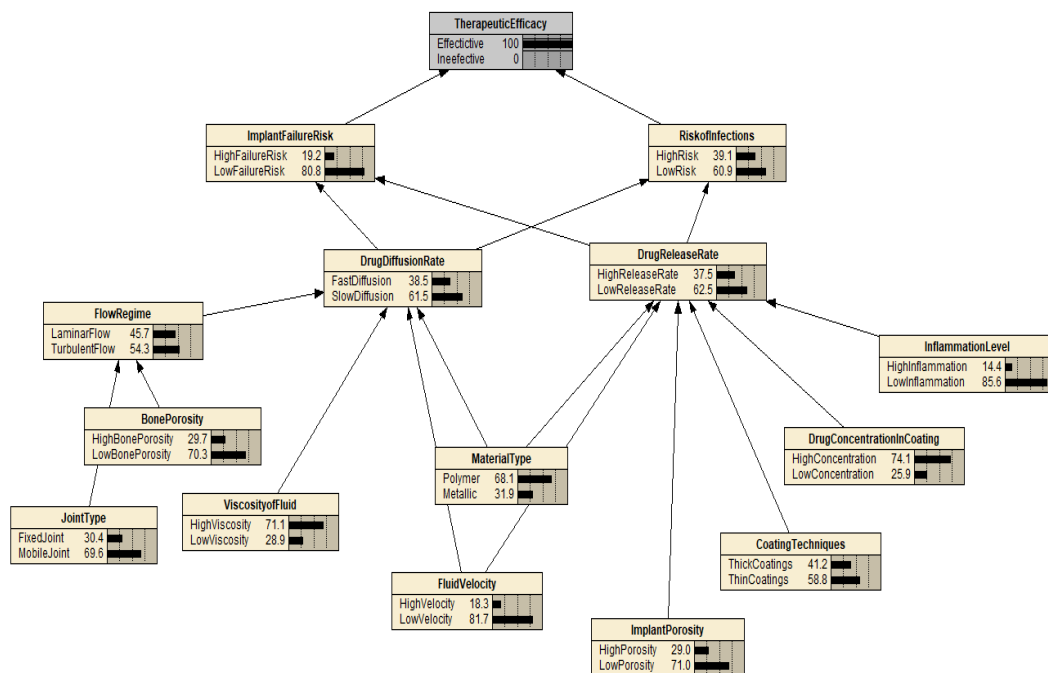


Figure 2: Bayesian diagnostic inference reasoning for evaluating fluid flow effects in drug-releasing orthopedic implants (therapeutic efficacy is effective = 100%)



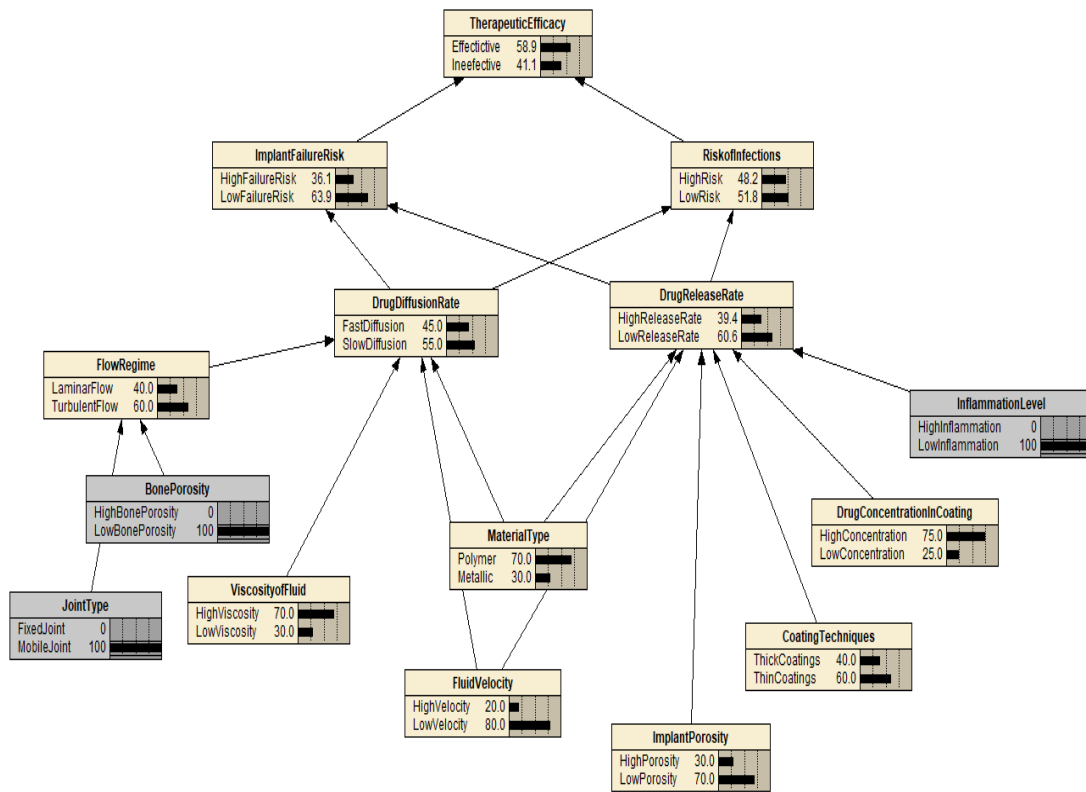


Figure 3: Patient-specific variable inference reasoning for evaluating fluid flow effects in drug-releasing orthopedic implants

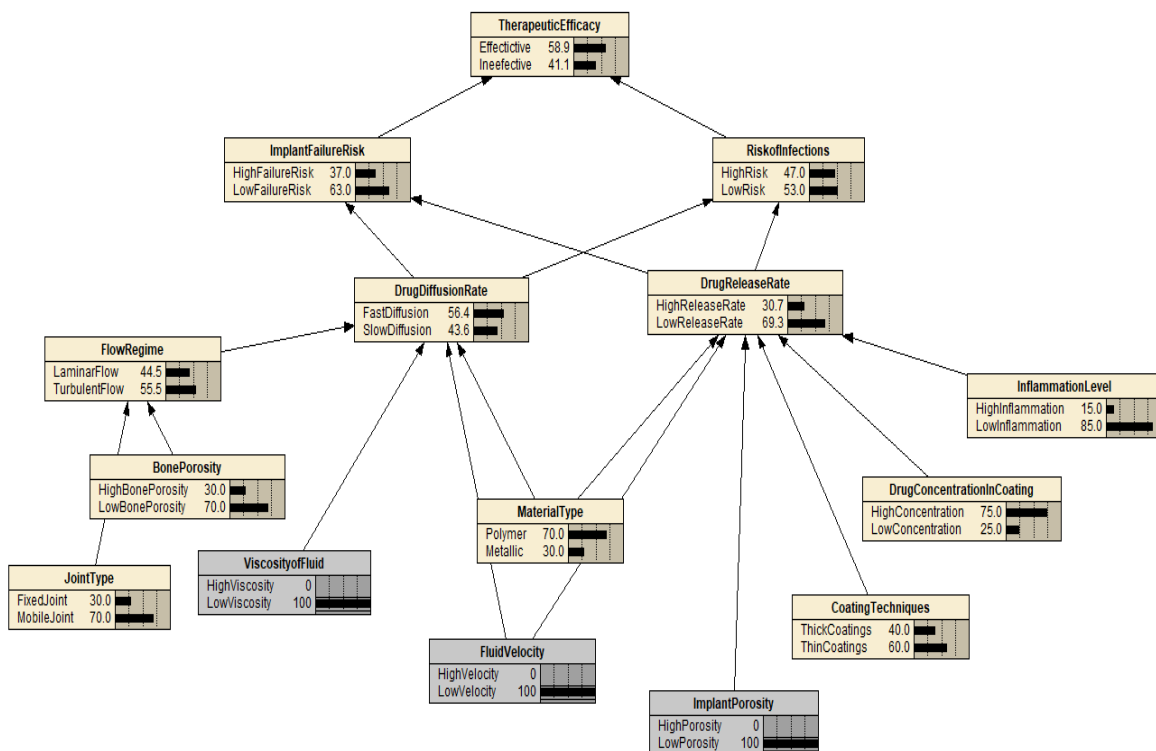


Figure 4: Fluid dynamics variable inference reasoning for evaluating fluid flow effects in drug-releasing orthopedic implants



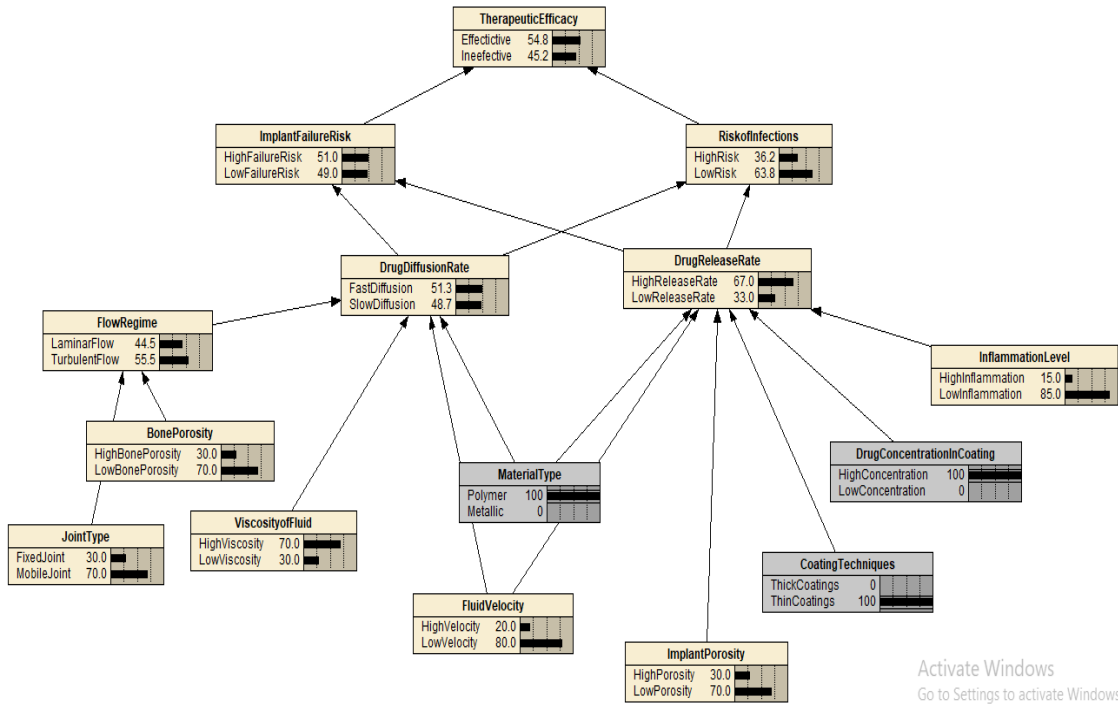


Figure 5: Implant design variable inference reasoning for evaluating fluid flow effects in drug-releasing orthopedic implants

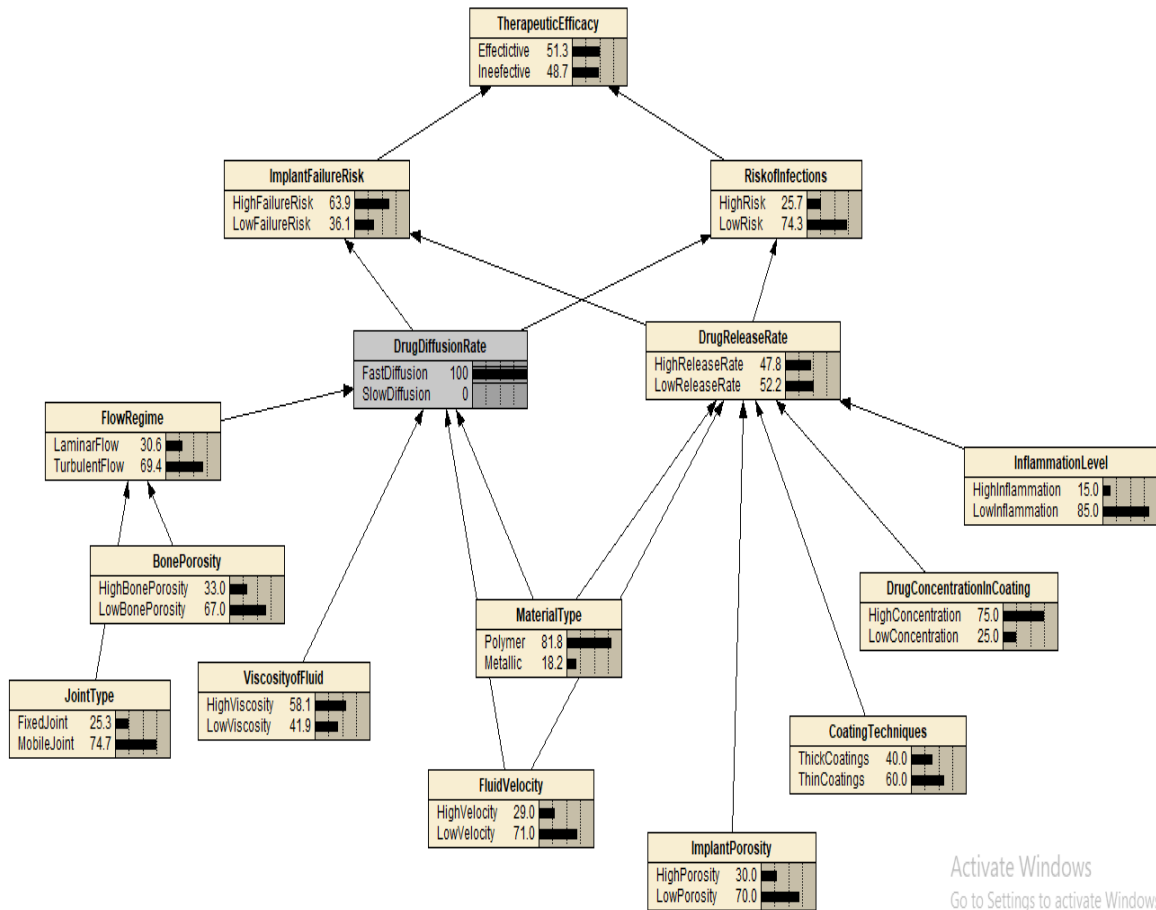


Figure 6: The effect of drug diffusion rate on fluid flow effects in drug-releasing orthopedic implants



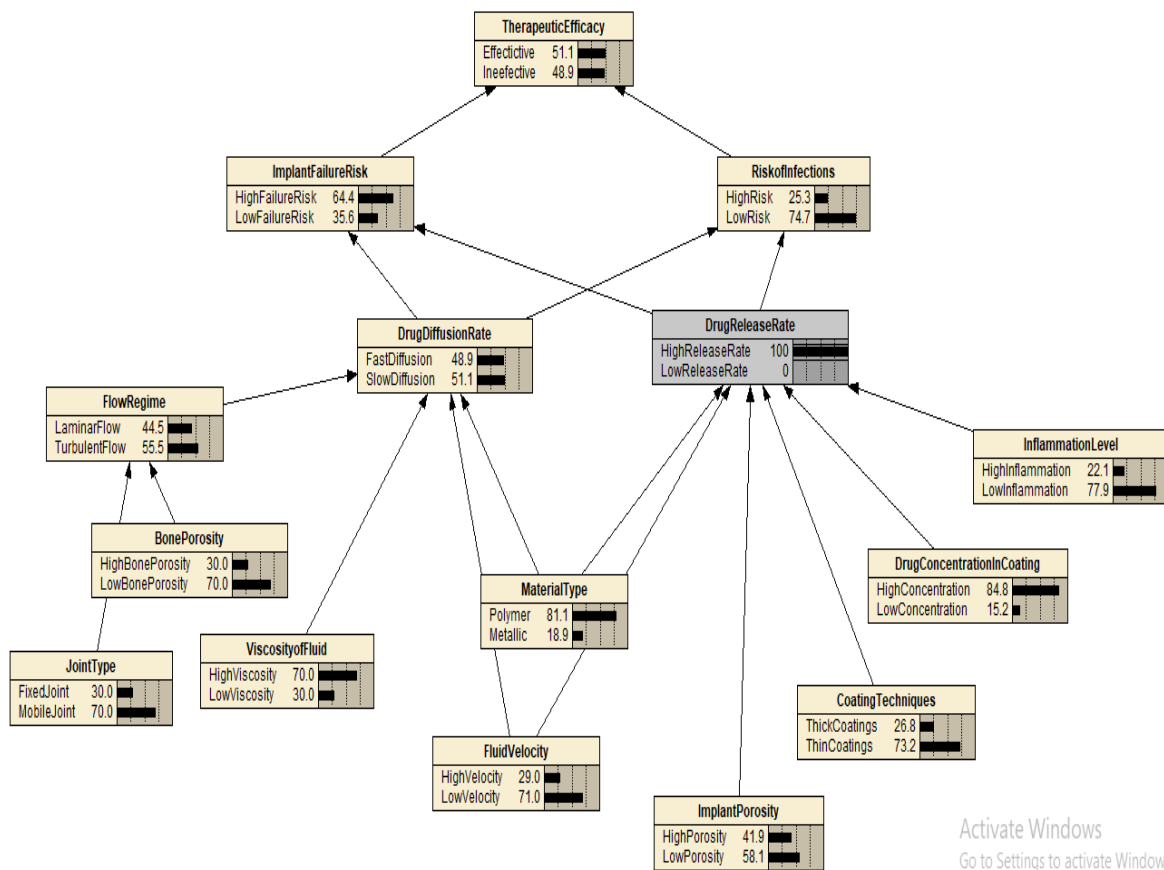


Figure 7: The effect of drug release rate on fluid flow effects in drug-releasing orthopedic implants

3.2 Discussions

The integration of Bayesian Belief Networks (BBNs) in modeling fluid flow effects in drug-releasing orthopedic implants, as demonstrated by this present research study, offers a novel approach to understanding the complex dynamics that influence drug dispersion at the implant-tissue interface.

Lietaert et al. [11] reported that patient-specific factors, biologically differences and implants material heterogeneity are uncertainly indicators which are not considered in deterministic modelling of fluid flow effect in drug releasing orthopedic implants. This has often lead to inaccuracies in the potential of predicting effective therapeutic efficacy. BBN model has been developed in this research study, which capture the uncertainty nature of fluid flow effect as well as the integration of expert opinion. Nine parent modes representing the root causal factors affecting effective therapeutic efficacy were identified namely; fluid velocity, implant porosity, viscosity of fluid, material type, coating techniques, drug concentration in coating, bone porosity, joint type and inflammation level. Bayesian causal influence showed that the probability of effective therapeutic efficacy is 58.6% while that of

ineffective therapeutic efficacy was 41.4%. This result revealed that BBN provides improved predictive activities and the significant challenge of the inherent complexity and variability in fluid flow in drug releasing orthopedic implants.

The nine Bayesian root causal factors were also categorized into patient-specific variables [1], fluid dynamics variables and implant design variables where Bayesian reasoning was done under each category. Fluid dynamics variable inference reasoning revealed the significant influence of fluid flow (laminar and turbulent) on drug releasing rate and drug diffusion pattern at the implant-tissue interface. This result is in agreement with work done by King et al. [4]. In the same vein the implant design variables inference reasoning revealed that thin coatings and high drug concentration are critical to increase drug release rate and this comes with an attendant shorter therapeutic durations. Similarly, King and McGinty [18] in their study reported similar results and postulated the need for optimal coating thickness that balances release kinetics. While high implants porosity is critical to fast diffusion of drugs, its mechanical stability is not guaranteed and the result of this present study also agrees with work done by Portillo-Lara et al. [19]



where the structural integrity of porous implants for drug delivery was reported. In addition, the implant design variables inference reasoning also revealed that polymer material is critical to controlled drug release and this is a result of good interaction with bodily fluid as reported by Eikani et al. [20].

Furthermore, the patient-specific variable inference reasoning revealed the effect of bone porosity, inflammation level and joint types on therapeutic outcomes. The Bayesian model predicts a 2.96% reduction in orthopedic implant failure when patient-specific variables namely bone porosity; inflammation level and joint type were observed. This result has overcome the challenges reported by Geiger et al. [10] when deterministic modeling technique was used to model the synovial fluid movement and variations in bone porosity and in joint implants. In addition, the significance of this study is the design of an optimised and controlled drug-releasing orthopedic implant that is effective based on probabilistic prediction of fluid dynamics, patient-specific and implant design variability. The BBN model revealed how implant failure and risk of infection can be reduced as well as how the therapeutic efficacy can be improved by accounting for uncertainty that is not considered when using deterministic models. As shown in Figure 2, the Bayesian diagnostic inference revealed the following as critical factors influencing fluid flow effect, namely inflammation level, implants porosity, viscosity of fluid, fluid velocity and bone porosity. The reduction in the probability of risk of infection and implant failure risk due to the consideration of uncertainty more predictable drug release patterns represents a significant advancement in orthopedic treatment strategies [20].

In comparison, this research study uses the methodology of Bayesian Belief Network (BBN) modeling technique to examine the combined effects of fluid flow, implant characteristics, and patient-specific parameters on drug-release behaviour in orthopedic implants to provide a probabilistic perspective that significantly contrasts with the deterministic models in previous studies. An example is King [6], in which the mathematical models of a standard nature were used to characterize diffusion, dissolution, and fluid-implant interactions, thus providing a high degree of accuracy in terms of time prediction but limited by the ability to cope with inherent uncertainty. The Bayesian paradigm followed herein specifically includes variability in bone porosity, state of inflammation, design of

coating, and fluid conditions, which produces a probabilistic estimate of therapeutic efficacy of 58.6%. Although King [6] effectively examines mechanistic transport mechanisms in detail, the current BBN model takes this effort further by establishing the probability of clinical outcome in changing biological and mechanical conditions.

An analytical solution of Adeleye et al. [8], applying the differential transform method, studied single and two-layered coating systems and found that the influence of the coating thickness, porosity and diffusion coefficients have a determinant effect on the concentration gradient. These results are consistent with the results of this current research study, which also refers to the coating thickness, implant porosity, and drug concentration among key determinants. However, the Bayesian belief network model does not only serve as a continuation of Adeleye et al. [8] with the confirmation of the relevancy of these variables but expounds on their interaction under uncertainty, i.e. making it evident that thin coatings in conjunction with higher drug concentrations are independent variables that significantly increases the likelihood of infection as well as the likelihood of implant failure. In contrast to Adeleye et al. [8] which provided quantitative descriptions of idealised situations, the Bayesian model presents trade-offs and quantifies the risk areas, thus forming the basis of more realistic clinical decision-making in a setting characterized by uncertainty.

Equally, the study of Lietaert et al. [11] on porous metals emphasizes the mechanical and biological consequences of porosity, where higher porosity leads to more fluid transport and at the same time reduces structural stability. This finding is consistent with the Bayesian approach finding that a high implant porosity increases the diffusion rate but it increases the risk of failure, as the Bayesian belief network shows a sharp increase of the probability of implant failure when the diffusion rate is too high. This current research study continues the descriptive analysis of biomaterials presented in Lietaert et al. [11] by quantifying the effect of patient-specific characteristics on the impact of material porosity on therapeutic response, i.e., the level of inflammation and the type of joint. Simply stated, although each of the mentioned previous studies is dedicated to one of the aforementioned aspects: coating physics, implant materials, or mechanistic modeling, the current research study is a synthesis of the above-mentioned dimensions into an uncertainty-aware predictive



system, thus providing a more comprehensive and clinically flexible understanding of the behavior of drug-release in orthopedic implants.

Finally, the creation of a probabilistic predictive tool that can calculate reliable intervals for concentration profiles and cumulative release is a significant contribution to existing knowledge thereby signifying a change from point predictions to uncertainty-aware implant design. Design tolerances, risk assessment, and regulatory decision making can all benefit from this framework.

4.0 CONCLUSION

The use of BBN to model fluid flow effect of drug release in orthopedic implant represents an important step towards addressing the complexities at the implant-tissue interface. This study has shown that BBN is a probabilistic method of modeling which has resolve the limitations encountered when using deterministic models such as finite element analysis for physiological system modeling. The BBN model developed has successfully model the uncertainty interrelationship between fluid dynamic factors, patient-specific factors and implant design factors in the prediction of a more accurate therapeutic outcome thereby enhancing the possibility of personalized medical applications. Nine factors affecting the therapeutic outcome of fluid flow effect in drug release orthopedic implant were identified namely fluid velocity, joint type, implant porosity, viscosity of fluid, material type, coating techniques, drug concentration, bone porosity, and inflammation levels while Bayesian causal inference estimated a 58.6% probability of achieving effective therapeutic efficacy.

The study highlighted the modeling of risks and challenges posed by the variability in fluid dynamics, patient-specific and implant design factors which mark a significant improvement over traditional models. This probabilistic method supports better clinical decision making process where clinicians and biomedical engineers can better predict and optimize drug release kinetics, minimize implant failure risks, reduce infection rates and design more effective orthopedic implants tailored to individual patient needs.

REFERENCES

- [1] Gaharwar, A. K. Peppas, N. A. Khademhosseini, A. “Nanocomposite hydrogels for biomedical applications.” *Biotechnology and Bioengineering*, vol. 111, no. 3, p. 441–453, 2014. <https://doi.org/10.1002/bit.25160>
- [2] Pearl, J. *Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference*. San Mateo, CA, USA: Morgan Kaufmann, 1988. (1st Ed.)
- [3] Taran, V. N. “Bayesian Belief Networks as a Tool for Modeling Hazardous Natural Processes.” In *Proceedings of the International Conference on Complex Systems (Complex Systems 2021, Lyon, France)*, CEUR Workshop Proceedings vol. 2834, p. 415–424, 2021.
- [4] King, D. McCormick, C. and McGinty, S. “How does fluid flow influence drug release from drug-filled implants?” *Pharmaceutical Research*, vol. 39, number. 1, p. 25–40, 2021. <https://doi.org/10.1007/s11095-021-03127-4>
- [5] Shi, Y. Wan, A. and Shi, Y. “Simulation study of the drug release dynamics.” *Proceedings of IEEE International Conference of Bioinformatics and Biomedicine (BIBM)*, Shanghai, China, p. 56-60, 2013. <https://doi.org/10.1109/BIBM.2013.6732735>
- [6] King, D. J. *Controlled Release of Therapeutics from Orthopaedic Implants*. PhD Thesis, University of Glasgow, 2020. <https://doi.org/10.5525/gla.thesis.81530>
- [7] Jain, A. King, D. Pontrelli, G. and McGinty, S. “Controlling release from encapsulated drug-loaded devices: insights from modeling the dissolution front propagation.” *Journal of Controlled Release*, vol. 360, p. 225–235, 2023. <https://doi.org/10.1016/j.jconrel.2023.06.019>
- [8] Adeleye, O. Ibrahim, A. and Yinusa, A. “Analytical study of single- and double-layer coating system for controlled drug-releasing orthopedic implants using differential transform method.” *Arid Zone Journal of Engineering, Technology & Environment*, vol. 20, no. 4, p. 947–958, 2024.
- [9] McGinty, S. and Pontrelli, G. “A general model of coupled drug release and tissue absorption for drug delivery devices.” *Journal of Controlled Release*, vol. 217, p. 327–336, 2015. <https://doi.org/10.1016/j.jconrel.2015.09.025>
- [10] Geiger, B. C. Grodzinsky, A. J. and Hammond, Paula T. “Designing Drug Delivery Systems for Articular Joints.” *Chemical Engineering Progress*, vol. 114, no. 5, p. 46–51, 2018. (<https://www.aiche.org/resources/publications/cep/2018/may/designing-drug-delivery-systems-articular-joints>).



- [11] Lietaert, K. Wauthle, R. and Schrooten, J. "Porous Metals in Orthopedics. In: *Biomaterials in Clinical Practice: Advances in Clinical Research and Medical Devices*, edited by Fatima Zivic et al., Springer International Publishing, Cham, Switzerland, p. 281–301, 2017. https://link.springer.com/chapter/10.1007/978-3-319-68025-5_10
- [12] Akinyemi, O.O. Adeyemi, H .O. Olatunde, B.O. Folorunsho, O. and Musa, M. B. "Bayesian Belief Network Modeling of Metal Lathe Machining Operations," *Mindanao Journal of Science and Technology*, 20(2), p. 71–87, 2022.
- [13] McLachlan, S. Dube, K. Hitman, G. A. Fenton, N. E. and Kyrimi, E. "Bayesian networks in healthcare: Distribution by medical condition," *Artificial Intelligence in Medicine*, vol. 107, article number 101912, 2020. <https://doi:10.1016/j.artmed.2020.101912>
- [14] Collins, R and Fenton, N, "Bayesian network modelling for early diagnosis and prediction of endometriosis," *medRxiv*, 2020. <https://www.medrxiv.org/content/10.1101/2020.11.04.20225946v1>
- [15] Semakula, H. M. Liang, S. Mukwaya, P. I. Mugagga, F. Nseka, D. Wasswa, H. Mwendwa, P. Kayima, P. Achuu, S. P. and Nakato, J. "Bayesian belief network modelling approach for predicting and ranking risk factors for malaria infections among children under 5 years in refugee settlements in Uganda," *Malaria Journal*, 22, article number. 297, p. 1-14, 2023, <https://doi:10.1186/s12936-023-04735-8>
- [16] Nordmann, J. P. and Berdeaux, G. "Use of a Bayesian network to predict the nighttime intraocular pressure peak from daytime measurements," *Clinical Therapeutics*, 29(8), p. 1751–1760, 2007, <https://doi:10.1016/j.clinthera.2007.08.012>
- [17] Guo, H. Wang, R. Wang, D. Wang, S. Zhou, J. Chai, Z. Yao, S. Li, J. Lu, L. Liu, Y. Xie, C. and Lu, W. "Deliver anti-PD-L1 into brain by p-hydroxybenzoic acid to enhance immunotherapeutic effect for glioblastoma," *Journal of Control Release*, vol. 320, p. 63–72, 2020, <https://doi:10.1016/j.jconrel.2020.01.005>
- [18] King, D. and McGinty, S. "Assessing the potential of mathematical modelling in designing drug-releasing orthopaedic implants." *Journal of Controlled Release*, vol. 239, p. 49–61, 2016. <https://doi:10.1016/j.jconrel.2016.08.009>
- [19] Portillo-Lara, R. Shirzaei, S. E. and Annabi, N. "Biomimetic Orthopedic Materials." In *Orthopedic Biomaterials*, edited by B. Li and T. Webster, Springer, p. 109–139, 2017. https://doi:10.1007/978-3-319-73664-8_5
- [20] Eikani, C. Hoyt, A. Cho, E. and Levack, A. E. "The State of Local Antibiotic Use in Orthopedic Trauma." *Orthopedic Clinics of North America*, 55(2), p. 207–216, 2024. <https://doi:10.1016/j.ocl.2023.07.003>

