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Integrating Bayesian Systems Modeling into an Industrial Engineering Capstone Course to Foster Students' Systematic Thinking

Md Ariful Islam, University of North Carolina at Charlotte

Dr. Yi Cao, UNC Charlotte

CAO Yi is a teaching assistant professor at William States Lee College of Engineering at the University of North Carolina at Charlotte. She earned her PhD from the Department of Engineering Education at Virginia Tech. She also worked as a research associate at the International Center for Higher Education Innovation(ICHEI), a UNESCO Category 2 Center for two years.

Dr. Lingxiang Yun, University of North Carolina at Charlotte

Dr. Lingxiang (Albert) Yun is an Assistant Professor in the Department of Industrial and Systems Engineering at UNC Charlotte. His research leverages artificial intelligence and machine learning to support data-driven decision-making in complex engineering systems. His areas of interest include sustainable and advanced manufacturing systems, energy system management, intelligent supply chain planning, and other related engineering applications.

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Abstract

Developing students' systematic and analytical thinking remains an essential but challenging goal in engineering education. These cognitive skills are critical for solving complex engineering problems that involve uncertainty, interdependence, and large amounts of data, yet they are often taught in isolation through disconnected tools or examples. Bayesian systems modeling offers a powerful framework for integrating key industrial engineering concepts such as uncertainty quantification, interdependence modeling, and data-driven decision-making. This paper introduces a project-based learning module designed for integration into a senior Industrial Engineering capstone course to support systematic reasoning through Bayesian multivariate spatial modeling. The proposed module may serve either as a full capstone project or as a structured reference example introduced at the beginning of the capstone experience, illustrating the expected depth of analysis, integration of multiple analytical tools, and systems-level reasoning within a realistic case study.

In the proposed module, students investigate how mobile phone, internet, and computer access are jointly distributed across multiple districts using Bayesian methods that explicitly account for spatial correlation and uncertainty. The project guides students through exploratory data analysis, regression modeling, spatial correlation analysis, Bayesian inference, and interpretation of posterior estimates and their credible intervals.

The module explicitly targets two ABET-aligned competencies: (1) formulating and solving complex engineering problems, and (2) designing and conducting experiments, analyzing data, and drawing evidence-based conclusions. Through Bayesian modeling in a socio-technical case involving digital access disparities, students apply engineering, mathematical, and data science principles while reinforcing quantitative and systems-level reasoning skills. The paper outlines the instructional context, implementation structure, student deliverables, and assessment strategy. By embedding probabilistic modeling into applied decision-making tasks, this work offers a transferable framework for integrating Bayesian reasoning into systems-oriented engineering education.

Keywords: Bayesian Systems Modeling, Capstone Course, Project-based Learning, Systematic Thinking

1 Introduction

Decision-making under uncertainty is a core competency in Industrial Engineering (IE), as professionals are routinely expected to design, analyze, and operate complex systems characterized by stochastic behavior, interdependence among components, and incomplete or noisy data. These challenges arise across a wide range of application domains, including manufacturing systems, supply chains, transportation networks, and socio-technical infrastructures [1], [2], [3]. As a result, developing students' ability to reason systematically and analytically under uncertainty is a critical objective of IE education [4].

Despite this importance, developing comprehensive, uncertainty-aware decision-making skills requires familiarity with a wide range of analytical tools, spanning fundamental probability theory and statistics, regression analysis, spatial or multivariate modeling, as well as more advanced topics such as Markov decision processes, queueing theory, and stochastic optimization. Due to the breadth of these topics, they are typically distributed across multiple courses over several years within many IE curricula. As a result, while students may become proficient in individual techniques, they may struggle to synthesize these methods into a coherent framework for analyzing complex and interconnected systems [5]. This separation of analytical content can limit students' ability to explain how technical, spatial, and contextual factors interact to shape overall system behavior.

Capstone courses provide an opportunity to address this challenge by integrating previously learned analytical concepts within open-ended, real-world problems [6]. In many IE programs, capstone projects provide students flexibility in defining problem contexts. While this openness supports creativity and ownership, ensuring that capstone experiences consistently promote systematic reasoning under uncertainty remains a pedagogical challenge. Without structured guidance, students may struggle to integrate multiple analytical methods into a coherent systems-level analysis. Providing a reference project framework can help guide students in structuring complex problems, selecting appropriate analytical methods, and interpreting results within an uncertainty-aware, systems-oriented perspective.

Bayesian systems modeling offers a natural foundation for such a reference framework by combining three capabilities relevant to IE practice: explicit quantification of uncertainty through posterior distributions, joint modeling of related outcomes, and representation of spatial dependence across units or regions [7], [8]. Rather than producing point estimates, Bayesian inference provides a distributional view of uncertainty and shows how information from one subsystem informs estimates of another, supporting reasoning about how uncertainty propagates through a system. Spatial priors, such as Conditional Autoregressive (CAR) structures, further enable examination of how geographic proximity or shared regional characteristics influence observed outcomes [7]. By working through a complete Bayesian workflow, from data preparation to model construction, inference, and interpretation, the reference framework demonstrates how to connect probabilistic reasoning with systems-level thinking.

This paper presents the design of a project-based learning module for an IE capstone course that employs Bayesian multivariate spatial modeling as a reference framework for systems-level analysis under uncertainty. The module uses publicly available, district-level digital access data to illustrate how mobile phone, internet, and computer access are jointly distributed and influenced by socio-economic and spatial factors. The proposed framework may serve either as a complete capstone project or as a structured reference example introduced at the beginning of the capstone experience to demonstrate the expected depth of analysis and integration of multiple analytical tools. The module has not yet been formally piloted, and thus it focuses on instructional design, competency alignment, and project structure rather than on empirical evaluation of student outcomes. The paper outlines the course context, learning objectives, project structure, and assessment plan. By embedding Bayesian systems modeling into an applied, case-based capstone framework, this work contributes a transferable instructional approach for integrating probabilistic reasoning and systems-level decision-making in IE education.

2 Background

2.1 Teaching Uncertainty in Engineering Education

Engineering education has long emphasized analytical methods for addressing uncertainty. Within IE programs, students are typically introduced to stochastic concepts such as random variables distribution, hypothesis testing, and regression analysis as foundational tools for descriptive analysis under uncertainty. These courses provide essential technical skills for quantifying variability from the basis to more advanced topics such as stochastic processes and decision analysis. Beyond foundational coursework, decision-making under uncertainty is also addressed through optimization, simulation, and operations research-oriented classes [8]. These approaches expose students to trade-offs, constraints, and performance evaluation under uncertainty, but they often rely on simplified assumptions or narrowly defined system boundaries. As a result, students may gain proficiency in applying specific techniques without fully examining how uncertainty propagates across interconnected components or how modeling assumptions influence system-level behavior [9].

Meanwhile, systems thinking has been introduced as a complementary perspective in engineering education. These courses use tools such as causal loops, system archetypes, and feedback models to help students move beyond step-by-step analysis and think about how systems behave over time. Through guided reflection and group discussion, students learn to question their assumptions, consider different perspectives, and understand how system boundaries and context shape outcomes [10]. This body of work highlights the importance of understanding relationships among system components rather than analyzing elements in isolation.

Despite these advances, uncertainty and interdependence are still frequently addressed in separate instructional contexts. Probabilistic modeling, decision analysis, spatial effects, and systems thinking are often taught in different courses, using different representations and assumptions. This separation can make it difficult for students to develop a unified perspective on how multiple forms of uncertainty interact and jointly shape system behavior. Prior studies point to a need for instructional approaches that integrate probabilistic reasoning and systems-level analysis within a single framework, enabling students to reason more effectively about complex, interconnected engineering problems [4].

2.2 Capstone Projects and Systems Integration

Capstone projects are widely used in engineering programs as a culminating experience intended to integrate knowledge acquired across the curriculum. In IE, capstone courses commonly involve open-ended, real-world problems that require students to formulate problem statements, select appropriate analytical methods, and interpret results within practical constraints. Prior studies emphasize the role of capstone projects in supporting synthesis across technical domains, particularly when problems involve multiple stakeholders, competing objectives, and complex system interaction [11], [12].

At the same time, the open-ended nature of capstone projects presents challenges for achieving consistent integration of analytical concepts. While flexibility in project selection supports student ownership and industry relevance, the shift from well-defined textbook problems to open-ended design can confuse students on how to combine their prior knowledge. As a result, it can also lead to uneven emphasis on systems-level analysis, with some projects focusing narrowly on isolated subsystems [13]. The literature suggests that capstone experiences benefit from common methodological expectations or guiding frameworks that help students connect individual analytical techniques and reason about interdependence across system components [14]. These observations point to the value of a structured analytical framework that illustrates how multiple tools can be integrated coherently within a complex engineering problem.

2.3 Bayesian Modeling in Engineering Education

Bayesian approaches are widely used in research and advanced applications for representing uncertainty, integrating information, and modeling dependence structures [15]. At the undergraduate level, students are commonly introduced to Bayesian probability concepts, such as conditional probability and Bayesian updating, within probability and statistics coursework [16]. Building on this foundation, Bayesian modeling supports joint representation of multiple related variables, hierarchical relationships, and spatial or contextual dependence. These characteristics allow diverse sources of information to be integrated coherently and enable uncertainty to be propagated across interconnected system components. In this way, Bayesian modeling serves as a suitable capstone-level analytical framework for integrating uncertainty analysis, optimization, and decision analysis while emphasizing synthesis of prior knowledge and reasoning about complex systems.

3 Capstone Module Description

3.1 Problem Description and Sources of Uncertainty

This module is structured around a Bayesian systems modeling case study that examines uncertainty in interconnected socio-technical systems using district-level digital-access data from the Multiple Indicator Cluster Surveys (MICS) 2019 [17]. The case study focuses on how mobile phone, internet, and computer access vary across regions and how these outcomes are shaped by spatial, socio-economic, and technological factors. The module first establishes the sources of uncertainty inherent in the real-world system and then distinguishes them from uncertainty introduced through analytical modeling.

System uncertainty reflects variability and heterogeneity in real-world conditions that influence observed outcomes. In the context of digital access, such uncertainty comes from multiple interacting factors, including household-level behavior and device usage, variation in access to mobile, internet, and computer technologies, geographic proximity and shared regional vulnerabilities, and socio-economic differences across districts. These factors jointly contribute to spatially structured patterns in digital-access outcomes, illustrating how system behavior emerges from the interaction of contextual, technological, and spatial drivers rather than from any single variable.

In addition to system-level uncertainty, modeling uncertainty is present because analytical models necessarily provide simplified representations of complex systems. Sources of modeling uncertainty considered in the case study include parameters estimated with error, missing or unobservable variables, structural assumptions embedded in the model, simplified functional relationships, and limitations in data availability or quality. Distinguishing between system uncertainty and modeling uncertainty provides a basis for interpreting probabilistic model outputs and understanding the limits of inference in complex, data-driven analyses.

3.2 Bayesian Modeling Approach

Building on the characterization of system and modeling uncertainty, the module introduces a Bayesian multivariate spatial modeling framework to analyze interdependent digital-access outcomes. The framework jointly models three correlated district-level indicators, mobile phone access, internet access, and computer ownership, using data from MICS 2019, allowing shared drivers and mutual dependence among outcomes to be represented explicitly. Spatial dependence across districts is incorporated to capture geographic clustering and regional effects that influence access patterns. Within this formulation, uncertainty is represented probabilistically through posterior distributions of model parameters and outcomes, providing a coherent basis for examining interdependence, spatial structure, and uncertainty propagation in complex socio-technical systems.

3.3 Project Workflow

The module is organized around a two-phase analytical workflow that guides the project from problem formulation to uncertainty-aware decision support: (1) Model Construction and (2) Bayesian Inference and Interpretation. This structure mirrors how complex socio-technical systems are analyzed in practice, guiding students step by step from preparing real data and building a model to see how data preparation, modeling choices, uncertainty, and spatial patterns jointly shape conclusions, rather than viewing analysis as a collection of disconnected techniques. The project workflow includes the following two phases.

Phase 1 is model construction, which begins with formulating a systems-level question focused on how digital-access outcomes vary across districts and where significant inequalities or spatial patterns arise. The digital-access problem is framed as a probabilistic system in which several related outcomes vary jointly across districts. Students work with household level indicators aggregated to district level from the MICS 2019, which includes information of mobile access, internet access, and computer ownership of households. A key instructional focus in this phase is data preparation. Students need to clean and preprocess the data by handling missing responses, managing outliers, standardizing variable definitions, and constructing spatial identifiers needed for defining district adjacency matrices. These steps emphasize that modeling decisions begin with how data are organized and represented.

After data preparation, students focus on model building. Rather than analyzing mobile, internet, and computer access separately, the module introduces a multivariate Bayesian framework that treats these indicators as interdependent outcomes observed across neighboring districts. This model structure allows students to explicitly represent uncertainty, cross-outcome dependence, and spatial autocorrelation within a single system. Spatial dependence is incorporated using CAR priors, which encode adjacency-based relationships and allow information to be shared across neighboring regions, following established practices in spatial statistics and disease mapping [18]. Through this phase, students learn how data preparation and model specification work together to represent complex systems more realistically than simpler, independent models.

Phase 2 is Bayesian inference, diagnostics, and interpretation. In this phase, students use the constructed spatial systems model to perform Bayesian inference and interpret results. Bayesian inference combines the prepared data with spatial priors to produce joint posterior distributions that quantify uncertainty, interdependence among outcomes, and geographic structure. Because these models do not have closed-form solutions, students apply Markov chain Monte Carlo (MCMC) methods, such as Gibbs sampling, to estimate model parameters in practice.

Diagnostic tools play a central role in this phase. Students can examine trace plots to assess convergence, use Moran's I to evaluate remaining spatial structure, and compare alternative model specifications using criteria such as the Deviance Information Criterion (DIC). Finally, students interpret posterior summaries and spatial maps to identify regional disparities, explore joint outcome patterns, and assess the influence of socio-economic factors. This phase emphasizes how Bayesian spatial models support evidence-based decision-making under uncertainty, enabling students to identify high-need regions, understand inequality, and reason carefully about system behavior [7], [19].

The workflow for our project is shown in Figure 1.

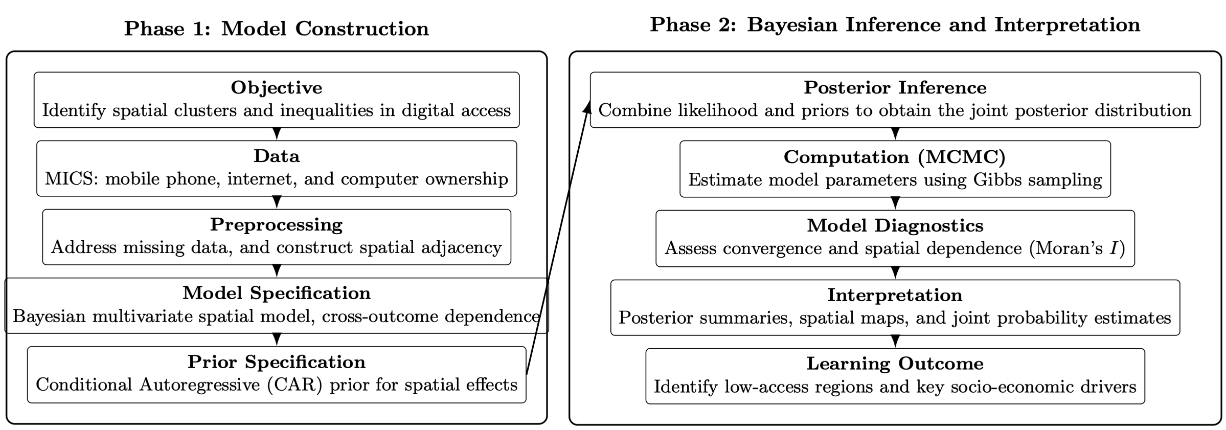

Figure 1. Project workflow

3.4 Illustrative Results

To demonstrate the types of analyses supported by the proposed framework, the module includes a set of illustrative posterior outputs derived from the Bayesian multivariate spatial model. These examples are intended to show how model results can be summarized and interpreted, rather than to report empirical findings. Figure 2 presents representative posterior distributions for selected socio-economic covariates, illustrating how coefficient direction, magnitude, and uncertainty are expressed through Bayesian inference.

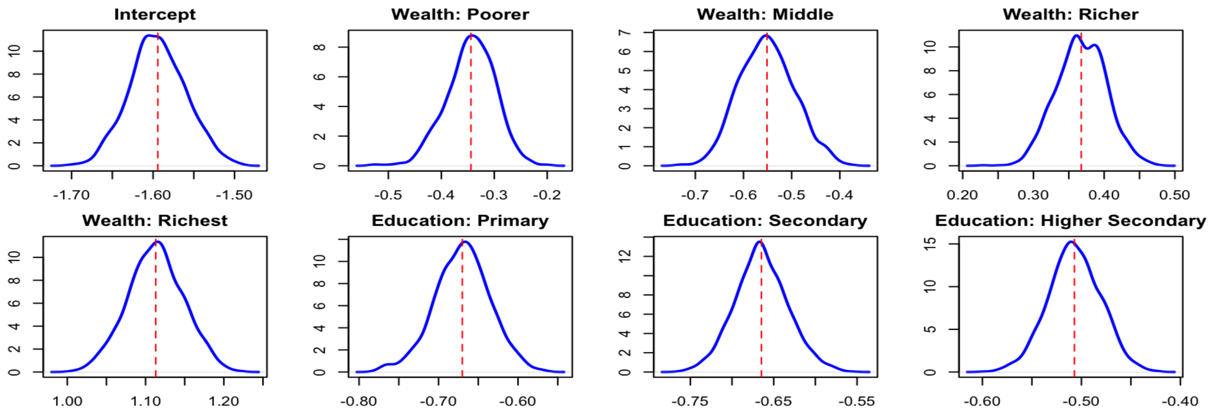

Figure 2: Posterior distributions for selected covariates from computer access

This figure displays smoothed posterior distributions for covariate parameters such as wealth index and education levels. The blue curves show the shape of each posterior distribution, and the red dashed lines mark the posterior means. Differences in distribution spread across covariates highlight how uncertainty varies depending on data support and model structure.

Illustrative posterior summaries are also provided in Table 1 for the three modeled outcomes: mobile access, internet access, and computer access. The posterior means reflect distinct access patterns across outcomes, with mobile access generally highest, followed by internet access and then computer ownership. Posterior standard deviations and credible intervals indicate greater uncertainty for less prevalent technologies.

Table 1: Illustrative posterior summaries

Variable	Posterior Mean	SD	95% CI	Spatial Variance (τ^2) Mean	Moran's I ($p< 0.05$)
Mobile Access (y_1)	0.84	0.05	[0.75, 0.93]	0.18	81%
Internet Access (y_2)	0.61	0.07	[0.48, 0.75]	0.45	86%
Computer Access (y_3)	0.42	0.06	[0.31, 0.55]	0.36	79%

Spatial effects further reveal structured regional patterns. Figure 3 presents the spatial effect for mobile access across districts after adjusting for socio-economic factors such as wealth and education. Red areas indicate districts with higher mobile access than expected, reflecting positive spatial effects, while blue areas indicate lower access than expected, reflecting negative spatial effects. Posterior spatial variance estimates and Moran's I statistics indicate meaningful spatial clustering for all three outcomes, with internet access exhibiting the strongest spatial dependence. This suggests that regional infrastructure and geographic proximity play an important role in shaping connectivity patterns.

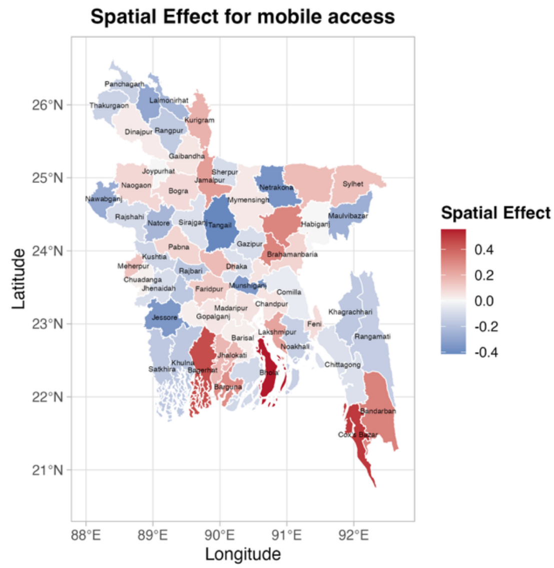

Figure 3: Spatial effect for mobile access across districts

Because outcomes are modeled jointly, the posterior distribution also enables examination of relationships among access indicators. Joint posterior summaries support computation of probabilities, correlations, and credible intervals for combined outcomes, allowing interdependence among technologies to be examined within a unified probabilistic framework. Together, these illustrative results demonstrate how Bayesian spatial models provide integrated insight into uncertainty, interdependence, and spatial structure in complex socio-technical systems.

4 Capstone Implementation

4.1 Capstone Course Context

The proposed module is designed for a senior-level IE capstone course that serves as the culminating design and analysis experience in the undergraduate curriculum. Students in this course typically work in teams of three to four on open-ended, student-defined projects under faculty supervision. The Bayesian modeling module can be introduced as either a prescribed project topic or a reference project framework that supports systems-level analysis under uncertainty. To use this framework as a prescribed topic, students are expected to complete courses related to statistics and regression analysis. Prior knowledge of Bayesian methods is helpful but not required, since the basic Bayesian concepts are introduced and reviewed within the module. The analytical tasks can be completed using programming tools such as Python or R, which requires students experience with these computational tools. If this framework is used as a reference framework, no specific prior knowledge is required for students.

Instructional support is expected to be provided through a combination of targeted lectures, advising meetings, and hands-on computational sessions. One weekly lecture is used to review relevant probabilistic modeling and systems-thinking concepts, while lab sessions focus on data processing, spatial analysis, and implementation of Bayesian inference. To support engagement with the modeling framework, the instructor can provide example datasets, starter code, and structured guidance as needed. Office hours and peer feedback sessions offer additional opportunities for discussion and clarification as teams interpret model outputs and refine their analyses.

4.2 Learning Objectives and Competency Alignment

The learning objectives of this capstone course are intentionally structured as an integrated and progressive sequence that reflects how industrial engineers engage with complex, data-driven systems in practice. Rather than representing isolated skills, the objectives form a coherent learning trajectory that moves from model construction, through technical evaluation, to contextual interpretation and decision-oriented reasoning.

The first objective establishes the analytical foundation of the course by requiring students to construct integrated probabilistic models that capture complex system behavior. This objective emphasizes the synthesis of multiple analytical elements such as, uncertainty quantification, spatial dependence, and joint outcome modeling, within a single modeling framework. In an industrial engineering context, this integration is essential because real-world systems are rarely governed by a single source of variability or a single outcome of interest. By focusing on unified model construction, the course ensures that students move beyond modular or sequential analysis and instead reason about systems as interconnected wholes.

Building directly on this foundation, the second objective shifts attention from model formulation to model evaluation and interpretation. Once an integrated probabilistic model has been constructed, students must be able to analyze its outputs from a technical perspective, including posterior distributions, spatial effects, and diagnostic measures. This objective logically follows the first because meaningful interpretation of uncertainty and model adequacy presupposes an understanding of how the model was structured and what assumptions it encodes. Together, the first two objectives emphasize technical rigor in both the creation and evaluation of analytical models, reinforcing the Industrial Engineering emphasis on data-driven problem solving under uncertainty.

The third objective extends this technical analysis into a broader socio-technical context, which is a defining characteristic of complex engineering systems. Students are expected to relate probabilistic modeling results to external contextual factors such as regional socio-economic conditions, spatial adjacency, and shared structural drivers across interdependent outcomes. This objective is logically dependent on the prior two: contextual interpretation is only meaningful when students can both construct credible models and critically assess their outputs. By explicitly requiring students to link quantitative results to real-world system characteristics, the course bridges the gap between statistical analysis and systems understanding, a core competency in industrial engineering practice.

The fourth objective represents the culmination of the learning sequence by requiring students to reason at the system level in support of decision-making. At this stage, students interpret probabilistic results not merely as technical outputs, but as evidence bearing on persistent vulnerabilities, regional disparities, and potential implications for policy or infrastructure interventions. This objective integrates and operationalizes the preceding objectives by transforming analytical and contextual insights into decision-relevant reasoning. The emphasis is not on prescribing specific solutions, but on demonstrating the ability to interpret uncertainty-informed results in a way that supports informed and defensible engineering decisions.

Collectively, these learning objectives emphasize the synthesis of students' prior analytical training, with particular focus on the interpretation and communication of uncertainty and the development of systems-level reasoning. Rather than prioritizing theoretical mastery of Bayesian methods, the course positions Bayesian modeling as an enabling framework through which students integrate multiple analytical tools and reason about complex, interdependent systems. This emphasis reflects the educational purpose of a capstone experience: to consolidate and operationalize previously acquired knowledge in service of structured problem solving, critical interpretation of results, and defensible engineering judgment under uncertainty.

Accordingly, the learning objectives align most directly with ABET Student Outcome 1, which concerns the ability to formulate and solve complex engineering problems by applying appropriate analytical and computational methods, and ABET Student Outcome 6, which emphasizes the ability to analyze and interpret data to support engineering decisions. Within the Industrial Engineering Mapping Matrix, the module explicitly foregrounds the integration of uncertainty analysis, systems modeling, and data-driven decision-making within a socio-technical context. This alignment underscores the role of the capstone module as a culminating experience that bridges technical analysis and real-world engineering practice, consistent with the core competencies expected of graduating industrial engineers.

4.3 Rubric and Assessment Strategy

Assessment is conducted using a rubric-based evaluation framework designed to support consistency, transparency, and alignment with program-level competencies. The assessment rubric was developed through backward alignment with the module's learning objectives and ABET Student Outcomes 1 and 6. It emphasizes structured integration of multiple analytical methods, explicit treatment of uncertainty, and systems-level interpretation of results. The evaluation criteria are designed to assess how effectively teams define system scope, integrate quantitative tools, reason about interdependence, and connect technical outputs to contextual and decision implications. In this way, the rubric supports assessment of coherent analytical synthesis rather than adherence to any single modeling technique.

Table 2: Assessment rubric

Category	Exceeds Expectations (4)	Meets Expectations (3)	Approaching (2)	Below Expectations (1)
A. Technical Modeling Work	Model correctly implemented; MCMC converges; spatial CAR effects applied properly	Model mostly correct with minor diagnostic issues	Some errors in model structure or estimation; partial diagnostics	Model incomplete, incorrect, or non-functional

B. Bayesian & Spatial Understanding	Clear explanation of priors, posteriors, uncertainty, and spatial dependence	Basic explanation with minor conceptual gaps	Limited understanding; missing key Bayesian or spatial concepts	Little or no conceptual understanding demonstrated
C. Interpretation & Systems Thinking	Clearly defines system boundaries and scope; explains interdependence among outcomes; interprets uncertainty propagation; and connects results to contextual and decision implications.	Identifies major system components and interdependence; provides reasonable interpretation of uncertainty and contextual implications.	Limited recognition of system interactions; interpretation mostly technical with minimal discussion of uncertainty or context.	Interpretation isolated from system context; little or no evidence of systems-level reasoning.
D. Data Cleaning & Analysis	Data fully cleaned; accurate spatial weights; strong exploratory analysis	Some issues in cleaning or spatial setup; EDA acceptable	Incomplete cleaning or weak exploratory analysis	Major errors or insufficient data preparation
E. Communication & Presentation	Clear, well-organized report with strong visuals (maps, tables, figures)	Good organization; visuals adequate	Report unclear in places; visuals weak or incomplete	Poorly written or inadequate explanations

Specifically, systems thinking can be measured through analysis of the digital-access system as an interconnected probabilistic structure rather than as isolated outcomes. Performance indicators include: (1) clearly defining system scope by specifying district-level boundaries, modeled outcomes, and included socio-economic covariates; (2) articulating interdependence by explaining how mobile, internet, and computer access are jointly modeled and how shared covariates influence multiple outcomes simultaneously; (3) reasoning about uncertainty propagation by interpreting posterior distributions, spatial random effects, and hierarchical structure; and (4) linking probabilistic findings to regional disparities, spatial clustering, and potential infrastructure or policy implications.

The rubric is designed to align with the learning objectives outlined in Section 4.2 and with ABET Student Outcomes related to complex problem solving and data analysis. To evaluate the effectiveness of the module in supporting ABET Student Outcomes 1 and 6, future implementations will incorporate a structured measurement plan. This can include analysis of rubric-based performance trends, comparison with prior capstone projects not using the framework, and targeted assessment items examining students' ability to formulate complex problems and interpret probabilistic results. These measures would allow examination of how engagement with the Bayesian systems modeling framework influences demonstrated competencies related to problem formulation and data-driven decision-making.

4.4 Educational Implications

As a proposed instructional framework, this module offers several potential pedagogical and curricular implications for Industrial Engineering education. While the module has not yet been formally applied, its design highlights ways in which Bayesian systems modeling can support structured reasoning about uncertainty and interdependence in capstone contexts. Whether implemented as a full project or introduced as a reference model at the beginning of the capstone sequence, the framework establishes a concrete illustration of analytical depth, methodological integration, and systems-level reasoning. The following discussion outlines its implications from pedagogical, curricular, and broader educational perspectives.

From a pedagogical perspective, integrating Bayesian spatial modeling into a real-world case study has the potential to function as a cognitive scaffold. By situating probabilistic modeling within a meaningful socio-technical context, students may be better positioned to connect abstract statistical concepts to system-level interpretation. This design aligns with principles of problem-based learning, where analytical tools are embedded within authentic and context-rich problems rather than taught in isolation.

From a curricular standpoint, the framework aligns with ABET outcomes related to complex problem solving and data-driven decision-making. The module is intended to encourage reasoning with uncertainty, such as interpreting posterior distributions and credible intervals, rather than relying solely on deterministic point estimates. Such reasoning is increasingly important in modern engineering practice, where decisions must be made under uncertainty and interdependent system conditions.

Finally, the use of authentic, publicly available datasets may support broader engagement with societal and global challenges. By analyzing real infrastructure access data, students can potentially connect technical modeling with contextual and ethical considerations. In this way, the module design aims to integrate analytical rigor with systems awareness and socially informed engineering judgment.

5 Conclusion and Future Work

This paper presents a systems-thinking-based framework that integrates Bayesian modeling into a senior IE capstone context. Motivated by the need for engineers to reason about uncertainty, spatial structure, and interdependence in socio-technical systems, the proposed module combines probabilistic modeling, spatial analysis, and real-world data within a structured project framework.

The primary contribution of this work is the design of a capstone-ready framework that supports integration of multiple analytical tools for uncertainty-aware, systems-level analysis. The paper focuses on module structure, modeling workflow, and assessment design; it does not report empirical evaluation of student learning outcomes. Future work will involve piloting the module, collecting formative feedback, and exploring assessment instruments to examine how students engage with systems-level reasoning within Bayesian modeling tasks.

Reference

[1] L. Yun, D. Wang, and L. Li, "Explainable multi-agent deep reinforcement learning for real-time demand response towards sustainable manufacturing," *Appl. Energy*, vol. 347, p. 121324, Oct. 2023, doi: 10.1016/j.apenergy.2023.121324.

[2] K. Gholamizadeh, E. Zarei, M. Yazdi, and Md. T. Amin, "Applying Bayesian Networks to Safety Causation Analysis and Modeling in Socio-technical Systems: Bridging Theory and Practice," in *Safety Causation Analysis in Sociotechnical Systems: Advanced Models and Techniques*, E. Zarei, Ed., Cham: Springer Nature Switzerland, 2024, pp. 363–404. doi: 10.1007/978-3-031-62470-4_14.

[3] L. Yun and M. Han, "Reverse logistics network planning for cloud remanufacturing: Exploring additive manufacturing in the circular economy," *J. Clean. Prod.*, vol. 505, p. 145439, May 2025, doi: 10.1016/j.jclepro.2025.145439.

[4] A. Azad and E. Moore, "The Impact of Systems Thinking Education on Engineering Students' Approach to Real-World Challenges," presented at the 2025 ASEE Annual Conference & Exposition, Jun. 2025. Accessed: Jan. 15, 2026. [Online]. Available: https://peer.asee.org/the-impact-of-systems-thinking-education-on-engineering-students-approach-to-real-world-challenges

[5] D. Jonassen, J. Strobel, and C. B. Lee, "Everyday Problem Solving in Engineering: Lessons for Engineering Educators," *J. Eng. Educ.*, vol. 95, no. 2, pp. 139–151, 2006, doi: 10.1002/j.2168-9830.2006.tb00885.x.

[6] S. Howe and J. Wilbarger, "2005 National Survey Of Engineering Capstone Design Courses," presented at the 2006 Annual Conference & Exposition, Jun. 2006, p. 11.4.1-11.4.21. Accessed: Jan. 16, 2026. [Online]. Available: https://peer.asee.org/2005-national-survey-of-engineering-capstone-design-courses

[7] S. Banerjee, B. P. Carlin, and A. E. Gelfand, *Hierarchical Modeling and Analysis for Spatial Data*, 2nd ed. New York: Chapman and Hall/CRC, 2014. doi: 10.1201/b17115.

[8] L. Rabelo *et al.*, "Emerging topics for industrial engineering curriculum," *ASEE Annu. Conf. Expo. Conf. Proc.*, Jan. 2006.

[9] K. I. Rana and E. Moore, "Evaluating the Use of System Mapping Tools to Support Researcher Understanding of Knowledge Diffusion in the Bio-economy," presented at the 2025 ASEE Annual Conference & Exposition, Jun. 2025. Accessed: Jan. 15, 2026. [Online]. Available: https://peer.asee.org/evaluating-the-use-of-system-mapping-tools-to-support-researcher-understanding-of-knowledge-diffusion-in-the-bio-economy

[10] R. Bachnak and A. Mishra, *Systems Thinking with a Focus on Engineering*. 2025. doi: 10.18260/1-2--57183.

[11] A. Ritenour, C. Ferguson, P. Gardner, B. Banther, and J. Ray, "Collaborative Project-Based Learning Capstone for Engineering and Engineering Technology Students," *2020 ASEE Virtual Annu. Conf. Content Access Proceeding*, doi: 10.18260/1-2--34300.

[12] A. Shurin, N. Davidovitch, and S. Shoval, “The Role of the Capstone Project in Engineering Education in the Age of Industry 4.0 - A Case Study,” *Eur. Educ. Res.*, vol. 4, no. 1, pp. 63–84, Feb. 2021, doi: 10.31757/euer.414.

[13] P. Brackin, D. Knudson, B. Nassersharif, and D. O’bannon, “Pedagogical implications of project selection in capstone design courses,” *Int. J. Eng. Educ.*, vol. 27, no. 6, p. 1164, 2011.

[14] S. Howe and J. Goldberg, “Engineering Capstone Design Education: Current Practices, Emerging Trends, and Successful Strategies,” 2019, pp. 115–148. doi: 10.1007/978-3-030-17134-6_6.

[15] M. Khakifirooz, C. F. Chien, and Y.-J. Chen, “Bayesian inference for mining semiconductor manufacturing big data for yield enhancement and smart production to empower industry 4.0,” *Appl. Soft Comput.*, vol. 68, pp. 990–999, Jul. 2018, doi: 10.1016/j.asoc.2017.11.034.

[16] C. Batanero and R. Álvarez-Arroyo, “Teaching and learning of probability,” *ZDM – Math. Educ.*, vol. 56, no. 1, pp. 5–17, Feb. 2024, doi: 10.1007/s11858-023-01511-5.

[17] UNICEF and BBS, “Bangladesh Multiple Indicator Cluster Survey 2019.” 2019, Bangladesh:BBS. [Online]. Available: https://www.unicef.org/bangladesh/media/3281/file/Bangladesh%202019%20MICS%20Report_English.pdf

[18] J. H. Albert and S. Chib, “Bayesian Analysis of Binary and Polychotomous Response Data,” *J. Am. Stat. Assoc.*, vol. 88, no. 422, pp. 669–679, Jun. 1993, doi: 10.1080/01621459.1993.10476321.

[19] X. Tang, “A Bayesian Variable Selection Method with Applications to Spatial Data,” *Grad. Theses Diss.*, May 2017, [Online]. Available: https://scholarworks.uark.edu/etd/1956