In this dissertation, we study two emerging problems in operations management: split-liver transplantation-related allocation and learning problems, and financial data analytics. While the applications differ considerably, the underlying models are not entirely problem-specific. We utilize and improve methods from fields including queueing theory, optimal control, and machine learning.

In chapter one, we study the liver allocation problem, specifically concentrating on the potential benefits of split liver transplantation (SLT). SLT is an effective procedure that can save two lives of patients with end-stage liver diseases (ESLD) using one deceased donor liver. Despite SLT’s potential to expand the pool of available liver grafts and reduce the gap between liver supply and demand, SLT is only utilized for a small minority of recipients in the US. Barriers to increased utilization of SLT include surgical expertise, organ travel time/cold ischemia time, and the highly complex decision-making required for every transplant donor-recipient match. This chapter will focus on the analytical modeling of a deceased donor liver allocation system with SLT and whole liver transplantation and consider both efficiency and related fairness concerns. We will formulate a multi-queue fluid system, characterizing the donor-recipient size matching and the dynamically changing Model for End-Stage Liver Disease (MELD)/Pediatric End-Stage Liver Disease (PELD) scores of candidates on the waiting lists. Our formulation allows us to find the optimal donor-recipient matching decisions for our approximation model under various scenarios, and evaluate the performance of different organ allocation policies, under metrics such as the number of organs wasted, the number of patient deaths before/after transplant, quality-adjusted life years, etc., while ensuring the outcome variance and/or the probabilities of getting a transplant between candidate groups are within prescribed levels. In our numerical study, we compare our proposed policy with several other potential policies to evaluate the performance improvements of optimally using SLT. We also evaluate the effects of SLT in reducing disparity among candidate size groups in the multi-objective framework.

In chapter two, we study the liver allocation problem where medical learning in the performance of SLT takes place. SLT is rarely used in the United States, in part because few surgeons in the US have learned to perform SLT. One barrier for young surgeons to acquire the skills to perform SLT is the need to perform actual SLT surgeries to become proficient, and the lower success rate such early surgeries have. Further, because SLT is a delicate operation, even with practice some medical teams may still have only mixed success. This paper studies the donated liver allocation problem in a setting where surgeons with different potential abilities may learn SLT, becoming skilled over time. We formulate a multi-armed bandit (MAB) model, in which learning curves are embedded in the reward functions, to address the trade-off between discovering and developing talents (exploration) and utilizing a defined group of already-skilled surgeons (exploitation). To solve our MAB learning model, we propose the L-UCB, and QFL-UCB algorithms, all variants of the upper confidence bound (UCB) algorithm, enhanced with additional features such as learning, queueing dynamics, fairness, and arm dependence. We prove that the regrets of our algorithms, that is, the loss in total rewards due to lack of information about surgeons’ aptitudes, are bounded by $O(\log$
t). We also show they have superior numerical performance compared to standard bandit algorithms in settings where learning exists; this includes standard algorithms that “know” learning exists, but cannot use this information as efficiently as our algorithm does. From an application standpoint, our algorithms could be applied to help evaluate potential strategies to increase the proliferation of SLT and other technically difficult medical procedures. From a methodological point of view, our proposed MAB model and algorithms are generic and have broad application prospects.

In chapter three, we develop and utilize data-driven techniques to detect changes in financial health and life-changing events from transaction-level data provided by a collaborating financial institution in North America. A common hypothesis in the financial service sector is that life-changing events are times in which a customer is likely to be more receptive to new financial services. For example, a customer who marries may begin combining financial accounts with their spouse and embark on a new investment strategy; a customer diagnosed with health issues may consider applying for a medical loan. For a financial institution, being able to predict these life-changing events may be helpful in choosing the appropriate offers to make. Due to data privacy issues and regulatory requirements, financial institutions cannot utilize personally identifiable information or track customers’ social media accounts. Nevertheless, information about life-changing events may be encoded, latently, within the customer’s transaction history. For example, being able to detect the replacement of salary from one employer by another is a clear indicator of a new job; expenses at a retailer that specializes in infant furniture potentially indicate childbirth, and the addition of new account holders may reveal a new marriage. In summary, we try to identify and predict life events from transactional data to understand the financial state of a customer which drives their demand for financial services.