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USING SIMULATION TO EVALUATE OPERATIONAL TRADE-OFFS ASSOCIATED WITH THE USE OF CARE TEAMS IN SPECIALTY CARE SETTINGS

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ABSTRACT

New approaches for designing delivery of care in specialty outpatient clinics are emerging as a result of the use of care-teams and shared resources. However, questions remain surrounding how shared resources, e.g., exam rooms or support staff, should be allocated to balance the competing performance objectives in specialty care settings. We develop a discrete-event simulation model to evaluate resource allocation policies in an outpatient specialty clinic. Different resource allocation policies, ranging from fully dedicated to partially flexible to fully flexible for multiple resource types, are evaluated based on multiple performance measures. We find that a proposed policy based on strategic capping of flexibility achieves desired access to resources from a provider's perspective while also maintaining high utilization rates.

1 INTRODUCTION

In recent decades, there has been a steady shift from inpatient care to outpatient care in healthcare delivery which is evident from the narrowed gap between hospitals' inpatient revenue and outpatient revenue (Advisory Board 2019). Some of these changes are driven by patient preference as a result of cost of care, convenience, and advanced technology to support outpatient care (Abrams et al. 2018), while others include improved safety and clinical outcomes compared to inpatient care (Munnich and Parente 2018). Within a changing healthcare environment, healthcare systems are experiencing significant pressure to provide high quality care while containing costs, further motivating a shift towards outpatient care. Delivering high quality services is a cornerstone for outpatient care delivery settings and is challenging since available resources in the clinic are limited.

Meanwhile, recent information flow regulations in ambulatory care such as incorporation of electronic health records (EHR) have increased the administrative burden of care. In the outpatient setting, providers sought to divide their time between clerical and clinical tasks, which is associated with contributing to provider burnout (Vahdat et al. 2018). Increased administrative burden can have an adverse impact on number of patient visits, provider satisfaction, and patient satisfaction (West et al. 2018). To overcome these challenges and increase the operational efficiency in outpatient settings, many healthcare system clinics have employed a 'care team' model (Buljac-Samardzic et al. 2020; Miller 2018).

With the emphasis on coordination among providers from different disciplines and medical staffs, care team models are often referred to as 'best practice' in outpatient care delivery settings (Kaplan et al. 2015). Early evaluation of care team implementations has claimed that higher efficiency can be achieved through shifting the majority of administrative responsibilities from the physicians to well-trained clinical support staff (Parks 2016; Perna 2017).

The care team approach is an example of many innovations happening in delivering care in outpatient clinics. However, innovations are not only limited to care delivery design but, there are simultaneous innovations occurring in the technological aspect of delivering care as a response to the growing need for multispecialty care. Multispecialty care coordination may include co-locating clinics of various specialties in one location to provide 'one-stop' for various forms of care. Due to the growing demand of multispecialty care, clinics may face new challenges such as (i) allocation of limited resources efficiently and appropriately among various specialties and (ii) increased inefficiencies such as increased wait time, decreased number of visits and decreased patient or provider satisfaction (Vahdat et al. 2017). The need to maintain efficiency in complex care delivery environments encourages the use of technological advancements such as Real Time Locating Systems (RTLS). RTLS is an increasingly used technology in outpatient care as it offers promise in improving resource utilization and operational efficiency with flexible resource allocation opportunities (Slachta 2018; Midmark 2019; Siwicki 2019; Berg et al. 2019).

The notion of flexibility in manufacturing contexts has long been a research focus (Jordan and Graves 1995). Flexibility in outpatient clinic settings has also been shown to have beneficial implications from scheduling perspectives (Alvarez-Oh et al. 2018; Balasubramanian et al. 2012). However, little is known regarding the most effective means of balancing the benefits of a care team model and the efficiencies of shared resources. Evaluating this trade-off becomes particularly important in specialty outpatient clinics where there is significant heterogeneity in the patients seen, expertise available, and structure and duration of appointments. Therefore, to obtain insights on resource allocation policies in outpatient specialty clinic settings, this paper focuses on assignment of clinical support staff (Medical Assistants (MA)/Licensed Practical Nurses (LPN)) to care providers such as physicians and Advanced Practice Registered Nurses (APRN), and assignment of examination rooms to care providers and clinical support staff. Toward this aim, we studied a specialty clinic in a major academic health center. A discrete-event simulation of a specialty clinic was developed to understand the most effective policy for 1) support staff to provider assignments and 2) room to provider assignments to assess the operational trade-offs associated with care team models where resources are typically dedicated and inflexible and flexible resource allocation policies.

Further undergirding this work are differing perspectives of the benefits of various resource allocation policies by stakeholders. Often, regardless of care team implementation, providers may prefer to have dedicated resources such as support staff and exam rooms. This is largely due to their aversion to the risk of being "blocked" by patients of other providers. That is, in shared resource allocation schemes the possibility arises where other providers' patients may occupy shared resources thereby "blocking" other providers' access to them, resulting in providers waiting for resources to become available. Conversely, health system administration is often inclined to prefer flexible and shared resource allocation policies as they view this as an opportunity to increase the utilization of current resources. This research aims to advance the understanding of when certain resource allocation policies may be preferable with regard to multiple performance measures in specialty outpatient settings.

Simulation is uniquely qualified to generate and offer insights into questions surrounding resource allocation in healthcare settings. Specifically, discrete-event simulation models have shown significant promise in evaluating hypothetical operational changes and scenarios in outpatient care delivery settings (Giachetti et al. 2005; Guo et al. 2004; Jun et al. 1999; Rohleder et al. 2011), including recent applications (Guo et al. 2019; Morrice et al. 2018). However, while modeling care team process flows has been examined and of interest (Rohleder et al. 2010), the simulation model and analysis presented here aims to provide insight regarding the evaluation of multiple resource allocation strategies within the context of outpatient specialty care.

The remainder of this paper is organized as follows: we introduce and discuss the range of resource allocation policies evaluated in Section 2, in Section 3 we present the simulation model and describe the specialty clinic flow, Section 4 details the results from our simulation model experiments, and in Section 5 we make concluding remarks.

2 RESOURCE ALLOCATION POLICIES

In this paper we consider a MA to Provider ratio of 2:1 and Room to Provider ratio of 2:1, based on the best practices reported in the literature (Berg et al. 2010; Baril et al. 2014; Zhong et al. 2018; Hayward 2019).

Past studies showed that these ratios are efficient and generally consistent with the ratios in the clinic setting we studied. As a result, the number of providers, MAs and exam rooms included in our resource allocation policies are 4, 8, and 8 respectively. However, in order to show the interplay between care team assignment and physical space allocation, we relax these assumptions in subsequent experiments.

We considered three different exam rooms' assignment to providers as follows: (i) dedicated (fixed) assignment where two rooms would be exclusively assigned to one provider, (ii) partial assignment where there is a combination of dedicated assignment and sharing of rooms and (iii) no assignment where each provider can use any available room (also known as pooled assignment). Similarly, MA assignment to providers are considered in three ways: (i) dedicated assignment where the MA will only assist to the providers being assigned to, (ii) partial assignment where only a sub-set of MAs are shared among sub-set of providers and (iii) no assignment where all MAs are shared among providers and the first available MA will serve the provider requiring assistance. The simultaneous assignment of rooms and MAs to providers led to 9 different policies, as shown in Figure 1.

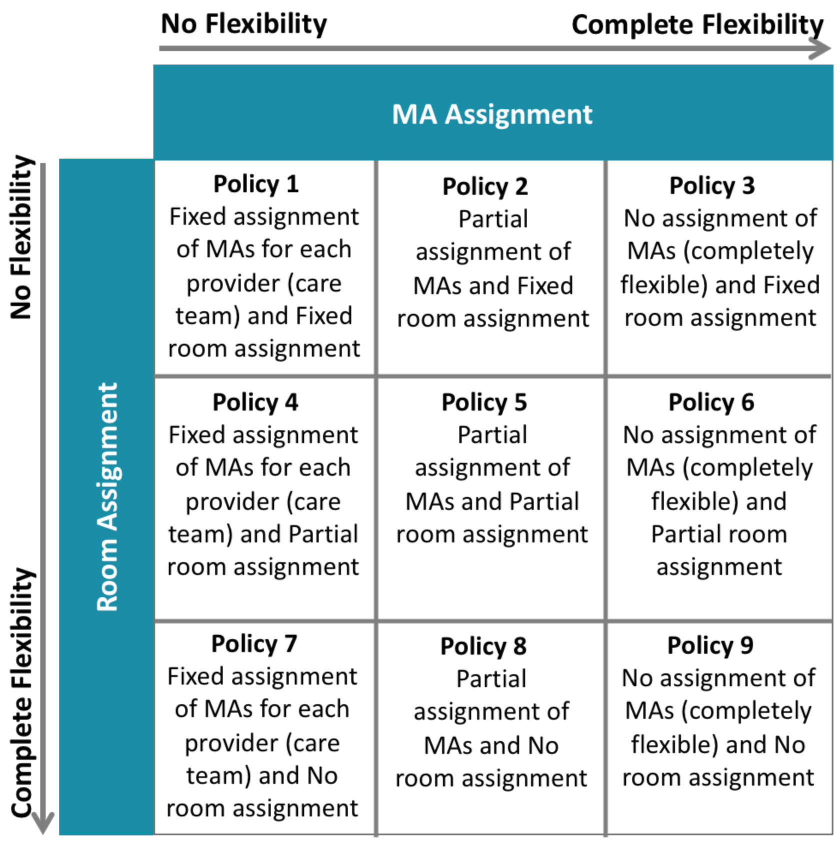

Figure 1: Nine combinations of policies for MA assignment and Room assignment for providers based on varied flexibility schemes.

As shown in Figure 1, flexibility in MA assignment increases as moving from left to right and flexibility in room assignment increases as moving from top to bottom. The room assignment policy is constant across Policies 1, 2 and 3 in which two exam rooms are exclusively assigned to providers however, MA assignment to providers varies: Policy 1 includes the assignment of two MAs to each provider, Policy 2 shows partial assignment, i.e., combination of MA assignment and sharing between the providers, and Policy 3 shows no assignment of MAs, meaning any provider can take help from any available MA.

Similarly, room assignment is constant across Policies 4, 5 and 6 in which the rooms are partially assigned to providers, i.e., each provider will have access to dedicated rooms and shared rooms. The MA assignment in Policies 4, 5 and 6 is the same as Policies 1, 2 and 3, respectively. Following the same pattern, the room assignment is constant across Policies 7, 8 and 9 in which there is no assignment of rooms to providers and the MA assignment policy is same as Policies 1, 2 and 3, respectively. The visual representation of these nine policies is shown in Figure 2.

As shown in Figure 2, Policy 1 includes four divided areas where in each area there are two rooms and one care team. For example, in the first division, Provider A has two assigned MAs, 1 and 2, and together they form a care team. This care team has access to both Room 1 and Room 2. Policy 2 shows two divided areas where in each area there is a fixed assignment of rooms to providers. However, MA assignments are partial. For example, the upper division shows that MA 1 is exclusively assigned to Provider A and MA 2 is exclusively assigned to Provider B. However, MAs 5 and 6 are shared between Providers A and B. Furthermore, the room assignment is fixed the same as Policy 1 where Rooms 1 and 2 are exclusively assigned to Provider A and therefore, MAs working with Provider A have access to these rooms.

Similarly, Rooms 3 and 4 are exclusively assigned to Provider B. In Policy 3, the room assignment is fixed the same as Policies 1 and 2 in which two rooms are exclusively assigned to each provider. For example, Provider A has exclusive access to Rooms 1 and 2. However, the MA assignment is completely flexible meaning all MAs are shared resources between all the providers. As MAs are completely shared resources in Policy 3, they are shown in the Common Area which indicates that any provider can use help from any available MA.

In Policy 4, two MAs are exclusively assigned to each provider which forms four different care teams. For example, MAs 1 and 2 are exclusively assigned to Provider A which forms one care team. However, the room assignment policy is partially flexible meaning each provider has a dedicated room. However, they also have access to two more shared rooms. For example, Room 1 is exclusively assigned to Provider A and Room 2 is exclusively assigned to Provider B. However, Rooms 3 and 4 are shared between Providers A and B. Due to this arrangement, the care team formed with Provider A has access to Rooms 1, 3 and 4. In Policy 5, the room arrangement is the same as Policy 4. However, the MA assignment policy is partially flexible, meaning one MA is exclusively assigned to one provider. This provider also has access to two more shared MAs. For example, MA 1 is exclusively assigned to Provider A, MA 2 is exclusively assigned to Provider B, and MAs 5 and 6 are shared between Providers A and B. In Policy 6, the room assignment is same as Policy 4 and 5, which is a partial assignment. The MA assignment, on the other hand, is completely flexible, i.e., all the MAs are shared between all four providers and, therefore, are shown under the Common Area.

The flexible room assignment is constant across Policies 7, 8 and 9 however, the MA assignment varies in all three policies. In Policy 7, there are four care teams as in Policy 1 and Policy 4, as shown in Figure 2. These care teams are shown under the Common Area because the room assignment is completely flexible. This means that any care team can use any available room. In Policy 8, each provider has an exclusive access to one MA but also has access to two shared MAs same as Policies 2 and 5. For example, MA 1 is exclusively assigned to Provider A, MA 2 is exclusively assigned to Provider B, and MAs 5 and 6 are shared between Providers A and B. In Policy 9 there is no assignment of MAs or rooms. All MAs and providers are shown under the Common Area which represents that any provider can use help from any available MA and any available room.

3 SIMULATION MODEL

The simulation model of the outpatient specialty clinic was developed using Arena (Kelton et al. 2015) based on a clinic in M Health Fairview's Clinic and Surgery Center. Patients arrive to the clinic based on a random arrival process with each provider having their own stream of assigned patients. Though the clinic

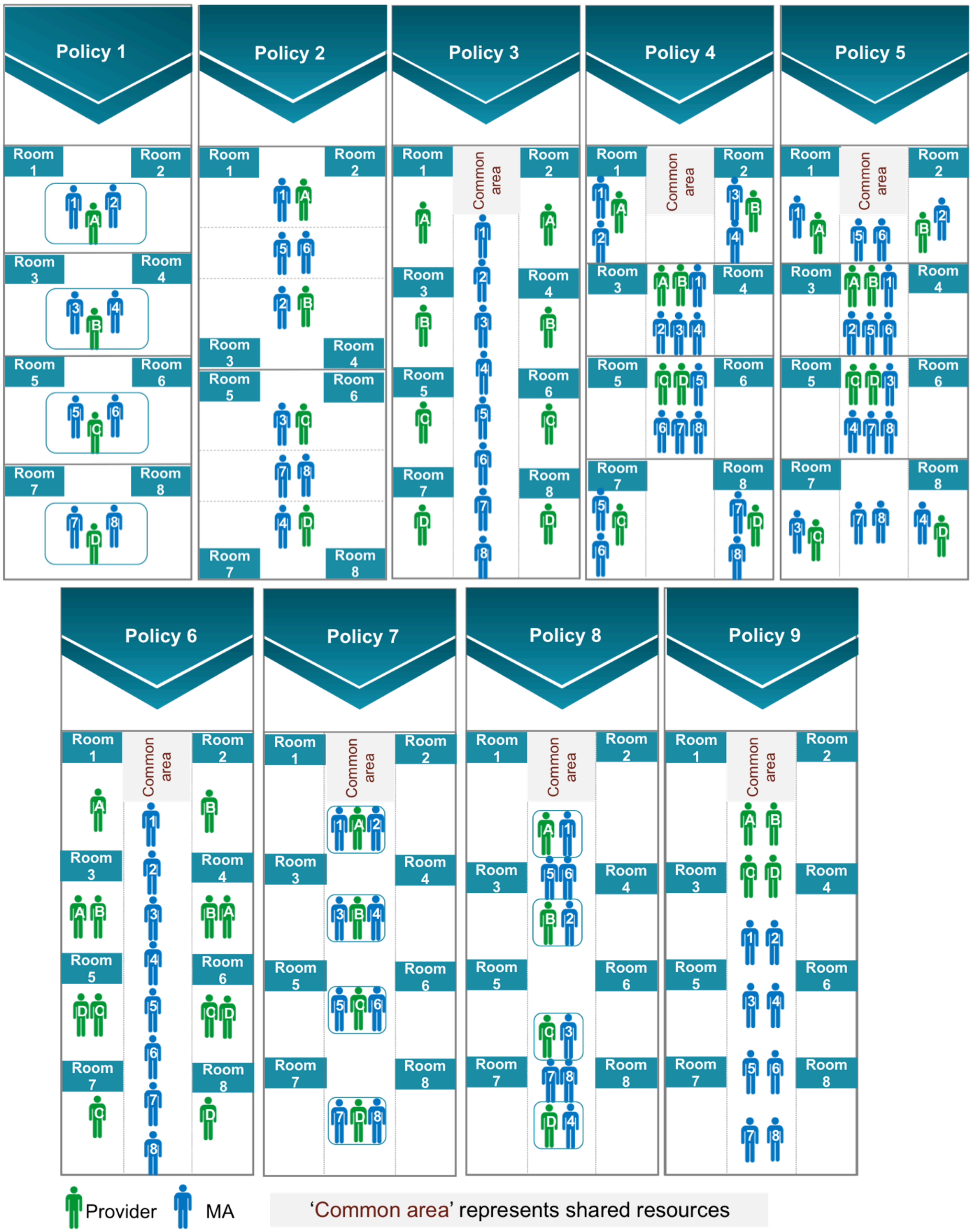

Figure 2: Visual representation of nine policies.

schedules patients' appointment times, early arrivals, tardiness resulting from upstream service delays, and variability in provider appointment templates all lead to an arrival rate which is appropriately modeled as random. Patients appointments are scheduled between 7AM and 4PM. The clinic plans on having its last patient finishing by 5PM. Based on this goal, one of the performance measures in the results are the percentage of patients who leave the system by 5PM. No-shows are accounted for at the beginning of the model based on the clinic's historical no-show rate. Upon arrival, the MAs are notified based on the patient's RTLS badge being within the clinic's reception area proximity. If an appropriate exam room is available, the assigned MA rooms the patient and does intake. Depending on the type of visit, the patient spends time with a nurse for a nurse-only visit. If the patient has an appointment with their provider, this occurs following the MA or nurse visit. After the visit with their provider, the patient may have an ancillary visit, e.g., with a nutritionist, social worker, etc. We note that the patient continues to occupy the exam room during each of these visits. Concluding the patient's visit, the MA finishes the appointment with the patient and escorts them out. The simulation model's flow is presented in Figure 3.

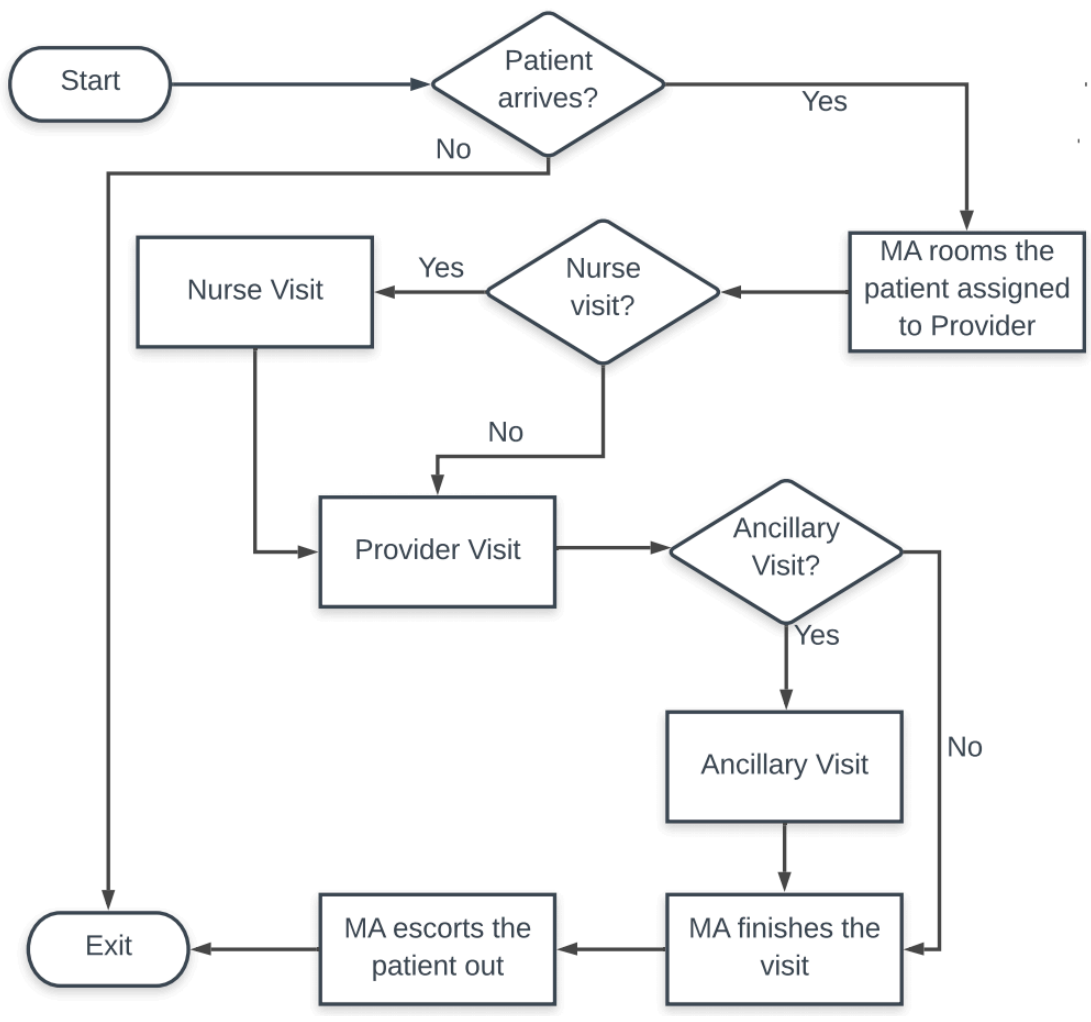

Figure 2: An overview of the simulation model of the multidisciplinary clinic demonstrates the patients' flow through the system.

Input parameters and distributions were based on both historical data as well as expert opinion from the care setting. Patient arrival processes are based on provider appointment template interarrival times.

Intake, nurse visit, MA visit, ancillary visit, and check out times were each modeled as having triangular distributions where clinic staff provided estimates for the respective minimum, maximum, and most likely durations. Provider visit durations were modeled as a discrete distribution as different providers allocate different appointment durations for both new and returning patients. New patient visits had durations of 20, 30, or 40 minutes while returning patient visits had durations of 10, 15, or 20 minutes. The number and allocation of MAs and exam rooms evaluated were based on the policies described in the previous section. The simulation model was validated with staff and data from the outpatient specialty clinic at the M Health Fairview's Clinics and Surgery Center. The simulation model was verified with clinic staff in its flow, logic, and performance measure output. Simulated patient length of stay, i.e., average patient time in clinic, was compared to the same durations as measured by historical RTLS data. The results from the simulation model closely matched those of the RTLS data.

4 RESULTS

Results presented are based on 1,000 replications of each model. The simulation results obtained for the resource allocation policies are compiled in Table 1 and are referred to as the base case set of results. We note that in the tables throughout the paper we use green shading to identify results were a positive increase is desirable and blue shading where a decrease is desirable. The analysis of these results shows a few interesting patterns explained further in this section. First, the average room utilization increases with increased flexibility in room assignment as we move from Policy 1 to Policy 9, which is an intuitive result of rooms not being assigned to specific providers and, therefore, are available to more providers, which in turn results in increased room utilization. Interestingly enough, the results associated with other outcomes become worse as the flexibility in room assignment increased as depicted in Table 1. Average provider utilization and average completion percentage decrease as we go from top (Policy 1) to down (Policy 9). Additionally, average wait time increases with increased flexibility in room assignment as we move from Policy 1 to Policy 9. We suspect that the flexibility induced room blocking and resulted in a decline of certain performance measures. Furthermore, average MA utilization is very low and is consistent across various policies. From these results, it is apparent that room utilization might be acting as a bottleneck here and, therefore, we designed subsequent experiments (Experiment 1) discussed further in this section.

The next set of experiments were designed to verify that a flexible room assignment policy could be acting as a bottleneck and, therefore, we increased the Room to Provider ratio from 2:1 to 3:1 including 12 rooms for 4 providers and keeping other variables consistent with the base case. The nine policies were evaluated, and results are compiled in Table 2.

Similar to the base case, the average wait time in Experiment 1 also increases as we move from Policy 1 to Policy 9. However, the average wait time associated with each policy is lower than its counterpart in the base case. Additionally, the difference between the average wait time values associated between Policy 1 and Policy 9 in Experiment 1 is significantly less than that in the base case. Additionally, the analysis of other performance measures shows that the values associated with all the outcomes, except average room utilization, are superior than the values in base case shown in Table 1. These results support the hypothesis that room utilization could be a bottleneck in the base case and give credence to provider concerns about the risk of blocking under flexible resource allocation schemes.

The MA utilization rate was consistently low (~12%) in both the base case and Experiment 1, which encouraged us to study whether MAs were excess resources in the base case. We decreased the MA to Provider ratio from 2:1 to 1:1 by taking 4 MAs for 4 providers, keeping other variables consistent with the base case. The nine policies were evaluated in Experiment 2 and the results are compiled in the Table 3.

We observe that the values for all the outcomes were similar to the base case, however, average MA utilization nearly doubled. This indicates that MA to Provider ratio 1:1 is a reasonable option as it cuts down the number of MAs in half without adversely affecting any outcomes and this option is also economically favored. We note that this is counter to a popular notion in outpatient clinic settings where employing an abundance of support staff is a relatively low-cost investment toward improving operational efficiency. While in practice support staff may be redeployed in various functions, our results show that for certain outpatient configurations a ratio of 2:1 is likely too high. Though, the ideal ratio will largely depend on the flow of MA responsibilities within particular clinic settings.

Finally, we proposed an enhanced Policy 9 where resources simultaneously consumed by a single provider are strategically capped, or limited. We refer to this analysis as Experiment 3 in which scenarios were developed by imposing a strategic cap on the maximum number of rooms that could be used by each provider at any given time. We selected three different scenarios representing strategic caps set at 1, 2 and 3. Results were compared against the base case Policy 9, which can be considered as having a strategic cap of 0 in this experiment. In this experiment, Cap 1 indicates that the maximum number of rooms used allowable rooms for the providers at any given time are 2. We note that the flexible resource allocation by each provider at any given time cannot be more than 1. Similarly, the maximum limit for the rooms is 2 and 3 for Cap 2 and 3 respectively. The results obtained from this experiment are tabulated along with the base case Policy 9 in Table 4. The results in Table 4 indicate that the outcomes are better when maximum policy with a strategic cap of 2 results in performance measures that are either superior to, or comparative with, the best performing base case policies. This can be interpreted as identifying a *win-win* scenario where providers no longer risk being blocked and the specialty clinic as a whole improves performance measures.

Table 1: Summary of simulation results for the base sase set of policies.

	Policy #	Avg. Wait Time (Min)	Avg. Provider Utilization (%)	Avg. Room Utilization (%)	Avg. Completion Percentage (%)	Avg. MA Utilization (%)
Base Case	Policy 1	32.63	66.90%	70.63%	89.75%	11.94%
	Policy 2	32.57	66.40%	70.19%	89.82%	11.85%
	Policy 3	32.62	66.26%	70.18%	90.16%	11.85%
	Policy 4	36.11	65.62%	76.32%	88.69%	11.79%
	Policy 5	36.58	65.79%	76.76%	88.66%	11.81%
	Policy 6	36.95	65.99%	76.96%	88.41%	11.89%
	Policy 7	40.77	64.02%	84.12%	86.67%	11.64%
	Policy 8	39.94	63.93%	83.86%	86.88%	11.62%
	Policy 9	40.76	64.04%	84.18%	86.54%	11.68%

Table 2: Summary of simulation results for experiment 1.

	Policy #	Avg. Wait Time (Min)	Avg. Provider Utilization (%)	Avg. Room Utilization (%)	Avg. Completion Percentage (%)	Avg. MA Utilization (%)
Experiment 1: Increase in Number of Rooms	Policy 1	27.31	67.90%	56.84%	92.24%	12.17%
	Policy 2	27.39	68.20%	57.18%	92.13%	12.22%
	Policy 3	27.80	68.41%	57.80%	92.27%	12.27%
	Policy 4	29.25	67.68%	62.45%	91.59%	12.24%
	Policy 5	29.41	67.83%	62.72%	91.28%	12.25%
	Policy 6	29.04	67.51%	62.13%	91.66%	12.18%
	Policy 7	28.83	67.40%	66.32%	91.21%	12.22%
	Policy 8	29.11	67.58%	66.58%	91.25%	12.25%
	Policy 9	29.26	67.26%	66.42%	91.34%	12.20%

Table 3: Summary of simulation results for experiment 2.

	Policy #	Avg. Wait Time (Min)	Avg. Provider Utilization (%)	Avg. Room Utilization (%)	Avg. Completion Percentage (%)	Avg. MA Utilization (%)
Experiment 2: Decrease in Number of MAs	Policy 1	33.17	66.55%	70.19%	89.76%	23.75%
	Policy 2	32.91	66.27%	70.15%	89.88%	23.66%
	Policy 3	33.33	66.25%	70.42%	89.85%	23.71%
	Policy 4	35.95	65.89%	76.40%	88.81%	23.67%
	Policy 5	36.86	65.73%	76.73%	88.45%	23.68%
	Policy 6	36.87	65.83%	77.00%	88.52%	23.64%
	Policy 7	40.45	64.47%	84.06%	86.85%	23.33%
	Policy 8	41.29	64.07%	84.27%	86.52%	23.28%
	Policy 9	41.24	64.17%	84.68%	86.29%	23.33%

Table 4: Summary of simulation results for experiment 3.

	Scenario	Avg. Wait Time (Min)	Avg. Provider Utilization (%)	Avg. Room Utilization (%)	Avg. Completion Percentage (%)
Experiment 3: Capping	Base Case	40.76	64.04%	84.18%	86.54%
	Cap set at 1	32.89	66.33%	70.27%	90.11%
	Cap set at 2	31.22	67.23%	79.97%	90.67%
	Cap set at 3	34.48	66.47%	83.00%	89.67%

5 CONCLUSIONS

In this paper we presented a simulation model motivated by the operational questions emerging from outpatient specialty care delivery domain. In particular, the model was developed to evaluate the operational performance trade-offs which exist as clinics consider care team-based designs and more flexible shared resource designs. In the care team-based approach resources, such as exam rooms and support staff, are fully dedicated to care providers as well as being collocated in many cases. This is in contrast to a fully flexible approach which may improve resource utilization and patient delays.

Based on the experiments discussed above, it is apparent that various room assignment policies significantly affect the performance measure outcomes. However, support staff assignment policies might not be as important if the room assignment policies are well designed. Further, we note that various room assignment policies do not affect the performance measure outcomes significantly when the healthcare facility is equipped with abundant resources. However, as discussed, the room assignment policies are an important consideration when the resources are scarce which is true for the majority of the cases in healthcare. An important takeaway for specialty clinic managers is that the use of a strategic capping policy was observed to be competitive with respect to all performance measures while having the added benefit of avoiding exam room blocking, which is often a high priority for providers.

However, we also note that this work has limitations which we aim to address in future work. Primarily, the evaluation of resource policies was based on specific ratios for exam rooms and support staff with respect to providers. While this is consistent with the practice studied and what we found in the literature, it is important to acknowledge that in academic medical centers it is common that these ratios may change on a day-to-day basis. While this motivates a broader question of the optimal number of providers and clinic size, more generally, one future direction for this work is identifying good resource allocation policies in clinical environments where the provider and resource levels may not necessarily be stationary over longer periods of time.

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REFERENCES

Abrams, K., A. Balan-Cohen., and P. Durbha. 2018. *Growth in Outpatient Care The Role of Quality and Value Incentive.* Deloitte Insights.https://www2.deloitte.com/content/dam/insights/us/articles/4170_outpatient-growth-patterns/di_patterns-of-outpatient-growth.pdf, accessed 16th April 2020.

Advisory Board. 2019. The Outpatient Shift Continues: Outpatient Revenue Now 95% of Inpatient Revenue, New Report Reveals. https://www.advisory.com/daily-briefing/2019/01/08/hospital-revenue, accessed 16th April 2020.

Alvarez-Oh, H. J., H. Balasubramanian, E. Koker, and A. Muriel. 2018. Stochastic Appointment Scheduling in a Team Primary Care Practice with Two Flexible Nurses and Two Dedicated Providers. *Service Science* 10(3):241-260.

Balasubramanian, H., A. Muriel, and L. Wang. 2012. The Impact of Provider Flexibility and Capacity Allocation on the Performance of Primary Care Practices. *Flexible Services and Manufacturing Journal* 24(4):422-447.

Baril, C., V. Gascon, and S. Cartier. 2014. "Design and Analysis of an Outpatient Orthopaedic Clinic Performance with Discrete Event Simulation and Design of Experiments". *Computers & Industrial Engineering* 78:285-298.

Berg, B., G. Longley, and J. Dunitz. 2019. "Improving Clinic Operational Efficiency and Utilization with RTLS". *Journal of Medical Systems* 43(3):1-9.

Berg, B., B. Denton, H. Nelson, H. Balasubramanian, A. Rahman, A. Bailey, and K. Lindor. 2010. "A Discrete Event Simulation Model to Evaluate Operational Performance of a Colonoscopy Suite". *Medical Decision Making* 30(3):380-387.

Buljac-Samardzic, M., K. D. Doekhie, and J. D. H. Wijngaarden. 2020. "Interventions to Improve Team Effectiveness within Health Care: A Systematic Review of the Past Decade". *Human Resources for Health* 18(1):2.

Giachetti, R. E., E. A. Centeno, M. A. Centeno, and R. Sundaram. 2005. "Assessing the Viability of an Open Access Policy in an Outpatient Clinic: A Discrete-event and Continuous Simulation Modeling Approach". In *Proceedings of the 2005 Winter Simulation Conference,* edited by M. E. Kuhl, N. M. Steiger, F. B. Armstrong, and J. A. Joines, 2246-2255. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Guo, M., M. Wagner, and C. West. 2004. "Outpatient Clinic Scheduling-A Simulation Approach". In *Proceedings of the 2004 Winter Simulation Conference,* edited by R .G. Ingalls, M. D. Rossetti, J. S. Smith, and B. A. Peters, 1981-1987. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Guo, J., T. Hoffman, A. Cohn, L. Niziol, and P. A. Newman-Casey. 2019. "Using Discrete-event Simulation to Find Ways to Reduce Patient Wait Time in A Glaucoma Clinic". In *Proceedings of the 2019 Winter Simulation Conference,* edited by N. Mustafee, K.-H. G. Bae, S. Lazarova-Molnar, M. Rabe, C. Szabo, P. Haas, and Y.-J. Son, 1243-1254. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Hayward, C. 2019. Physician Offices and Outpatient Clinics: How Many Exam Rooms? https://blog.spacemed.com/outpatient-clinics-how-many-exam-rooms/, accessed 19th April 2020.

Jordan, W. C. and S. C. Graves. 1995. "Principles on the Benefits of Manufacturing Process Flexibility". *Management Science* 41(4):577-594.

Jun, J. B., S. H. Jacobson, and J. R. Swisher. 1999. "Application of Discrete-event Simulation in Health Care Clinics: A Survey". *Journal of the Operational Research Society* 50(2):109-123.

Kaplan, G. S., M. H. Lopez, and J. M. McGinnis (Editors). 2015. *Transforming Health Care Scheduling and Access: Getting to Now*. Washington: National Academies Press.

Kelton, W. D., R. Sadowsky, and N. B. Zupick. 2015. *Simulation with Arena.* 6th ed. New York: McGraw-Hill, Inc.

Midmark. 2019. University of Minnesota Health Clinics and Surgery Center Patient Flow Optimization Case Study. https://www.midmark.com/docs/default-source/documents/midmark_rtls_um_clinics_and_surgery_center_case_study.pdf, accessed 16th April 2020.

Miller, C. J., B. Kim, A. Silverman, and M. S. Bauer. 2018. "A Systematic Review of Team-Building Interventions in Non-Acute Healthcare Settings". *BMC Health Services Research* 18(1):146.

Morrice, D. J., J. F. Bard, H. Mehta, S. Sahoo, N. B. Arunachalam, and P. Venkatraman. 2018. "Using Simulation to Design a Worklife Integrated Practice Unit". In *Proceedings of the 2018 Winter Simulation Conference*, edited by M. Rabe, A. A. Juan, N. Mustafee, A. Skoogh, S. Jain, and B. Johansson, 2624-2635. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Munnich, E. L. and S. T. Parente. 2018. Returns to Specialization: Evidence from the Outpatient Surgery Market. *Journal of Health Economics* 57:147-167.

Parks, T. 2016. Medical Assistants Take Central Role in Team-Based Health Care: One Stanford Practice. https://www.ama-assn.org/practice-management/payment-delivery-models/medical-assistants-take-central-role-team-based-health, accessed 16th April 2020.

Perna, G. 2017. Medical Assistants Play Vital Role in Innovative Practices. https://www.physicianspractice.com/survey-results/medical-assistants-play-vital-role-innovative-practices, accessed 19th April 2020.

Rohleder, T., T. Huschka, J. Egginton, D. O'Neil, and N. Woychick. 2010. "Modeling Care Teams at Mayo Clinic". In *Proceedings of the 2010 Winter Simulation Conference*, edited by B. Johansson, S. Jain, J. Montoya-Torres, J. Hugan, and E. Yücesan, 2304-2314. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Rohleder, T. R., P. Lewkonia, D. P. Bischak, P. Duffy, and R. Hendijani. 2011. "Using Simulation Modeling to Improve Patient Flow at an Outpatient Orthopedic Clinic". *Health Care Management Science* 14(2):135-145.

Siwicki, B. 2019. Real-Time Locating System Reduces Wait Times by 75% at Oregon Medical Group. https://www.healthcareitnews.com/news/real-time-locating-system-reduces-wait-times-75-oregon-medical-group, accessed 16th April 2020.

Slachta, A. 2018. Real-time Location Systems Streamline Workflow, Improve Patient Satisfaction. https://www.radiologybusiness.com/topics/imaging-informatics/real-time-location-systems-streamline-workflow-improve-patient, accessed 16th April 2020.

Vahdat, V., J. Griffin, S. Burns, and R. Azghandi. 2017. "Proactive Patient Flow Redesign for Integration of Multiple Outpatient Clinics". In *Proceedings of the 2017 Winter Simulation Conference*, edited by W. K. V. Chan, A. D'Ambrogio, G. Zacharewicz, N. Mustafee, G. Wainer, and E. Page, 2893-2904. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Vahdat, V., J. A. Griffin, J. E. Stahl, and F. C. Yang. 2018. "Analysis of the Effects of EHR Implementation on Timeliness of Care in a Dermatology Clinic: A Simulation Study." *Journal of the American Medical Informatics Association* 25(7):827-832.

West, C. P., L. Dyrbye, and T. D. Shanafelt. 2018. "Physician Burnout: Contributors, Consequences and Solutions". *Journal of Internal Medicine* 283(6):516-529.

Zhong, X., H. K. Lee, M. Williams, S. Kraft, J. Sleeth, R. Welnick, L. Hauschild, and J. Li. 2018. "Workload Balancing: Staffing Ratio Analysis for Primary Care Redesign". *Flexible Services and Manufacturing Journal* 30(1):6-29.

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