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Improving Healthcare Service Quality: A System Dynamics Approach to Managing Visit Times and Reducing Error Rates

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ABSTRACT

This study explores the application of system dynamics modelling to enhance service quality in healthcare systems. Healthcare environments are inherently complex, requiring adaptive strategies to address challenges such as fluctuating patient demands, work pressure, reduced visit times, and error generation in physician prescriptions. Through simulation-based analysis, we evaluated the impact of various policies, including adjustments to patient arrival rates and human resource hire/quit rate. Our findings indicate that reducing patient arrival rates effectively stabilises work pressure and minimises error generation, but it may conflict with organisational accessibility goals. Increasing human resources, particularly experienced employees, emerges as a sustainable alternative, enhancing service capacity and reducing errors. A dual strategy combining an increased hire fraction of experienced employees with retention-focused policies preventing the employee quit rate yields the most promising results. This approach improves employee efficiency, reduces error probabilities, aligns visit times with standards, and boosts profitability. The study underscores the importance of balancing workforce optimization with system costs to achieve long-term improvements in service quality. Simulation-based decision-making offers healthcare administrators a robust framework for evaluating the cascading effects of policy changes. By integrating dynamic modelling into management practices, healthcare systems can achieve enhanced operational performance, improved patient satisfaction, and sustainable service quality outcomes..

Keywords

System Dynamics, Error Generation, Visit Time, Healthcare Service Quality, Patient Arrival Rate, Human Resource Efficiency.

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1. Introduction

In healthcare systems, the quality of service is a multifaceted concept that significantly impacts patient outcomes and overall system efficiency. The World Health Organisation (WHO) defines quality of care as the degree to which health services increase the likelihood of achieving desired health outcomes, emphasising the importance of effectiveness, safety, and patient-centredness in delivering healthcare services (Fatima et al., 2018). This perspective emphasises that service quality is not merely about meeting standards but also involves ensuring that services are tailored to meet the individual needs and preferences of each patient. The quality of service is a critical factor that influences patient satisfaction and overall health outcomes (Younis, 2024; Coutinho et al., 2020).

Hence, healthcare administrators must implement robust policy-making strategies that focus on optimising service delivery without compromising quality. It includes training physicians in time management while maintaining thoroughness in patient interactions, as well as continuous monitoring of service quality metrics to identify areas for improvement (Begun et al., 2011; Adekugbe, 2024; Arabov et al., 2024). Ultimately, improving service quality in healthcare systems requires a holistic approach that integrates evidence-based practices with an understanding of the unique challenges faced by healthcare providers.

The quality of service encompasses various dimensions, including the time taken for patient visits, which can significantly affect both the efficiency of care delivery and the probability of errors made by healthcare providers. The complexities surrounding these issues are increasingly recognised in contemporary healthcare research (Younis, 2024; Coutinho et al., 2020).

A systematic review highlights that service quality in healthcare is inherently multidimensional, with factors such as tangibility, responsiveness, reliability, assurance, and empathy being essential for enhancing patient satisfaction. These dimensions are crucial as they directly relate to how patients perceive their interactions with healthcare providers and the overall care they receive (Singh and Prasher, 2019).

Healthcare systems and hospitals often face challenges in accurately forecasting the time required for patient care, which can result in numerous negative effects, starting with a fundamental inability to accommodate individual patient variability (Charan et al., 2024). Due to the complexity of system dynamics models arising from interdependencies, interactions, feedback loops, and nonlinear relationships interactive simulations offer a valuable way to explore various scenarios, policies, and decisions, making it possible to gain deeper insights into the behaviour of complex systems (Ebtekar et al., 2024). System Dynamics (SD) Modeling provides invaluable insights into understanding the dynamic complexity present in healthcare systems due to the interconnections between factors including health behaviours, environmental and socio-economic conditions, human service delivery infrastructures, medical innovations, health and social policy, disease progression and outcomes, and other health-related determinants, as these change about one another over time (Charan et al., 2024). The goal of applying SD models in healthcare is to highlight innovative approaches—such as stakeholder-engaged approaches—to simulation modelling, data analysis, and data use that enhance our understanding of the behaviour of complex systems, predict responses to policy interventions, and translate findings and discussions into actionable insights (Zabell et al., 2021).

SD models are mathematical representations based on causal feedback loops, with simulation at the core of their methodology. When the structure of a system is accurately modelled, the simulation results can reliably forecast its behaviour. Vensim is a commonly used tool for performing these simulations. The concept of system dynamics was introduced in the mid-1950s by Jay Forrester, a professor at the Massachusetts Institute of Technology, as an innovative approach to improving organizational performance. Researchers argue that the human mind struggles to understand the behaviour of social systems through simple linear thinking. Therefore, analyzing such systems requires the use of nonlinear, multi-loop feedback models. Through dynamic simulation, experts were able to uncover the underlying causes of operational issues at General Electric (Madady Nia et al., 2024).

SD models offer the potential to improve healthcare systems by enabling real-time adjustments to physician schedules and workloads, thereby enhancing efficiency and patient satisfaction. By using these models, healthcare providers can better align their clinical schedules with accurate time estimates for different diagnoses and procedures, leading to more efficient and patient-centred care (Musa et al., 2024). SD modelling involves the continual updating and monitoring of clinical prediction models. This method enables models to adapt over time as new data becomes available, ensuring their predictions remain accurate and relevant in the context of evolving health system dynamics. These models integrate information from multiple sources, such as patient history and ongoing health status, to provide more comprehensive and accurate predictions regarding physician visit times (Jenkins et al., 2021). Accurate simulation of health service challenges relies on several best practices designed to ensure realistic and effective modelling of complex healthcare environments. One critical approach involves the integration of simulation activities co-designed and delivered by a team of simulation experts

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in partnership with health service units, specifically targeting quality and safety goals (Rose et al., 2018).

The integration of dynamic systems into healthcare management facilitates a more comprehensive understanding of the interdependencies within healtcare clinical environments. An effectively designed simulation scenario offers a realistic and immersive experience, fostering critical thinking, teamwork, and problem-solving among participants. As highlighted by Wolstenholme (1993), this approach enables decision-makers to visualise how various factors, such as staffing levels, patient inflow, and appointment durations, interact over time, leading to more informed policy-making strategies aimed at improving service delivery. SD modelling offers valuable tools for understanding and addressing these complexities. By simulating various scenarios within healthcare systems, stakeholders can identify how changes in scheduling practices or resource allocation impact visit times and overall service quality. For example, studies have shown that implementing dynamic appointment scheduling can significantly improve access times and reduce patient wait times, ultimately enhancing service quality. Such approaches allow for flexibility in managing fluctuating patient loads while ensuring that healthcare providers can maintain in adequate interaction times with patients (Ala et al., 2019).

In Primary Health Care (PHC), maintaining sufficient visit times is vital for ensuring patient safety and satisfaction. Key variables in SD models of physician visit times typically include patient arrival times, consultation durations, and scheduling strategies (Kyarisiima et al., 2024). Extending visit times can lead to increased patient waiting times and longer working hours for physicians. The discrepancies between expected and actual service times can create a "death spiral" effect within healthcare settings. This phenomenon occurs when reduced interaction times lead to rushed assessments, resulting in misdiagnoses and compromised patient safety. The implications of this are significant; as service quality declines, patient trust erodes, further exacerbating the challenges faced by healthcare providers (Alizadeh-Zoeram et al., 2019).

Simulation can be a practical tool for quantifying these impacts and guiding decision-making. The use of simulation not only enhances medical and nursing education by improving knowledge, skills, and behaviour but also supports patient safety and risk management. It helps healthcare professionals identify and correct potential sources of error, thereby improving safety and clinical outcomes (Makhni and Hennekes, 2023). Recent studies have highlighted the complexities associated with managing visit times, particularly in dynamic healthcare environments where patient demand and provider availability fluctuate (Joseph et al., 2024; Alnajjar, 2024).

Experimental studies have sought to determine how varying the visit time of outpatient clinical encounters affects the quality of healthcare. These studies manipulate visit times to assess their impact on several dimensions of care quality, including effectiveness, efficiency, timeliness, safety, equity, patient-centeredness, and patient satisfaction (Araujo et al., 2020; Younquoi et al., 2023; Farooqi et al., 2024). A systematic review by Hajebrahimi et al. (2019) emphasizes that insufficient consultation time not only affects the accuracy of diagnoses but also diminishes patient satisfaction and trust in healthcare services. This finding is typically recommended for outpatient consultations. When actual visit times fall below this standard, it can create a cycle of rushed appointments and heightened risks of errors, leading to a phenomenon described as a "death spiral" in service quality. Specifically, the study emphasises that when physicians adhere to standard visit times, there is a notable reduction in the potential for errors during consultations. Conversely, when actual visit times fall short of the standards, it can lead to increased error rates and a decline in service quality (Hajebrahimi et al., 2019). A study by Swathi and Barkur (2023) underscores the importance of integrating patient-centred approaches into service delivery models, which can help mitigate the complexities associated with time management in clinical settings. By focusing on the nuances of patient-provider interactions and fostering an environment where adequate time is allocated for each consultation, healthcare organisations can enhance both service quality and patient outcomes. Another study published in BMC Primary Care examined the impact of shorter (15-minute) primary care appointments compared to longer (30-minute) appointments on healthcare utilisation within seven days following the initial appointment. The findings suggested that limiting the time spent with patients when evaluating acute health needs could adversely affect the quality of care and increase subsequent healthcare utilisation, such as ambulatory reassessment, emergency department care, and hospitalisation.

Additionally, an observational study examined the temporal regularity of primary care visits and their impact on patient outcomes. This study used Medicare claims data from 378,862 fee-for-service Medicare beneficiaries who received primary care at federally qualified health centres over four years. The results indicated that more regular primary care visits were associated with better patient outcomes, highlighting the importance of consistent and proactive care.

In summary, understanding the intricacies of service quality in healthcare necessitates a SD approach. Such an approach not only highlights existing problems but also facilitates the development of targeted interventions that enhance both patient care and operational efficiency. This introduction provides an overview of the importance of visit time in healthcare service quality while referencing recent studies that validate these claims within the context of SD modelling.

This study aims to utilise the SD approach to effectively manage various variables, including human resources, patient arrival rate, work pressure, error generation, and visit time, in order to combat the decline in service quality and ultimately enhance the quality of medical services. This study introduces a novel approach by examining the interconnections between key variables in a healthcare service system, analysing how work pressure, visit time, error rates, and workforce hire and quit rates interact dynamically. By modelling these relationships, the research predicts system behaviour over time and highlights the reinforcing feedback loops that sustain inefficiencies and quality erosion. The study demonstrates how increased work pressure reduces visit time, leading to higher error rates, increased rework, and a continuous rise in patient quantity. To address this, managers may adjust human resource levels, considering the balance between rookie and experienced employees. While hiring increases efficiency over time, a high workforce quit rate can negatively impact overall system performance, worsening the problem.

Furthermore, this research evaluates various policy interventions, including workforce hiring and reduction strategies, as well as patient intake management, to mitigate work pressure and enhance service quality. By simulating these dynamics, the study offers valuable insights into the long-term effects of policy decisions, enabling managers to design strategies that enhance efficiency, control costs, and maintain service quality in healthcare systems.

The study is structured as follows: It begins with the development of a conceptual model based on a dynamic hypothesis and a causal loop diagram. Next, the relationships among variables are represented through a stock-and-flow diagram. Finally, the completed model is applied in a healthcare clinic, where the impact of various human resources policies and employees' hiring and exit rates on service quality is examined. The study identifies and recommends effective policies to overcome the decline in quality.

2. Methodology

In this research, a system is considered based on the Alizadeh-Zoeram et al (2019) model. To gain a clear understanding of the developed model, it is applied in a hospital clinic setting with their data. The analysis examines explicitlythe physicians working during one of the clinic's shifts. The primary concern identified in this clinic relates to the behaviour of visit time per service. According to the clinic's standards, the standard duration for each patient visit is approximately 18 minutes. However, the actual time per service falls short of this standard due to work pressure. While this discrepancy might appear minor, the SD approach aims to demonstrate that this seemingly simple issue involves significant complexities. So, the system experiences a "death spiral," where the time allocated for each service an essential indicator of service quality—continually decreases. Addressing this problem through policy-making introduces additional layers of complexity.

To study the system dynamically, the following four main steps are implemented using the Vensim DSS V6.4 software environment.

3. Modelling problem: Dynamic hypothesis and causal loop diagram

The dynamic hypothesis outlines the system’s framework and explains its evolving behaviour over time (Madady Nia et al., 2024). In this study, the dynamic hypothesis related to service quality, with a focus on patient visit time, is finalised after incorporating insights from the literature and expert feedback. The hypothesis is as follows:

In a healthcare service system, when work pressure increases, the visit time per service for each person falls below the desired level. It triggers two primary responses:

Employees (physicians) attempt to address the situation by reducing the visit time spent per service below the standard level. This adjustment increases the rate of task completion and increases the patient’s quit rate. However, shortening service time (patient visit time) increases the likelihood of error generation, leading to more rework. This rework amplifies the rework rate and further increases work pressure (a reinforcing loop).

The reduction in visit time compared to the standard time, along with the rise in errors (such as prescription mistakes), signals a decline in system quality. To address this issue, known as the 'death spiral of quality,' managers may decide to adjust their human resources and productivity to address the problem, thereby attempting to mitigate work pressure and quality erosion.

Therefore, managers may increase hiring rates to match the desired level of human resources, thereby improving human resource efficiency. If the workforce is categorised into two groups—rookies and experienced employees—with differing input/output rates in efficiency, over time, rookies gain experience, and their efficiency improves. This dynamic increases the total efficiency, reducing error generation and, subsequently, work pressure.

Conversely, hiring new employees (rookies) while experienced employees leave the system can lower overall efficiency. This reduction increases the probability of errors, leads to increased rework, and expands the error backlog, thereby exacerbating work pressure. On the other hand, hiring experienced and rookie employees imposes costs on the system, and consequently, profit decreases.

The outlined relationships in the dynamic hypothesis are represented in detail through a causal loop diagram (Figure 1). Arrows illustrate the relationships between variables, with positive (+) or negative (–) signs assigned to indicate polarity. A positive relationship means that the cause and effect move in the same direction, while a negative relationship indicates the opposite.

As shown in the figure below, two reinforcing loops exist in the causal loop diagram. The larger loop, labelled as the **reinforcing loop W/E,** demonstrates that as the number of patients increases, work pressure rises, leading to shorter visit times. It, in turn, results in an increase in prescription errors, ultimately causing a rise in the rework due to patients returning for corrections, which further increases the number of patients. The smaller loop, labelled as **reinforcing loop P/E**, illustrates that when the number of patients increases, their outflow also grows, which again contributes to higher error generation and rework.

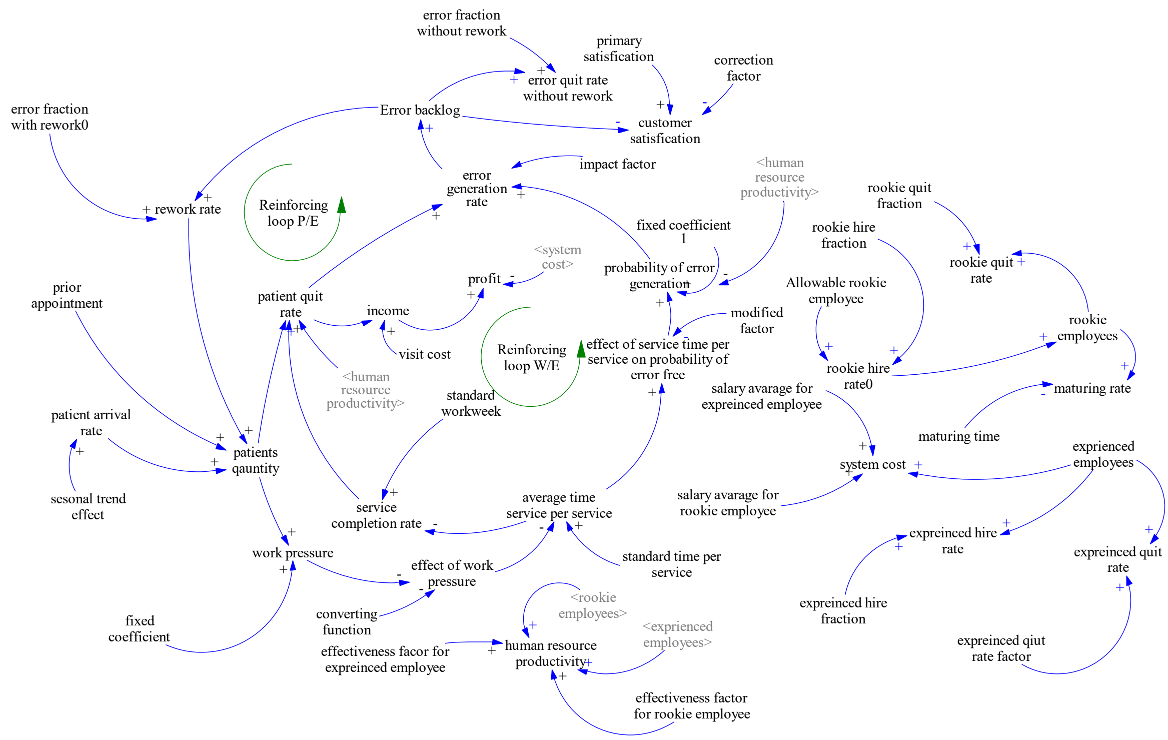

Figure 1. Causal loop diagram

4. Stock and flow diagram

The stock/flow diagram is divided into two main parts: the human resources subsystem and the patient quantity and error generation subsystem, shown in Figure 2. Also, detail is described as follows:

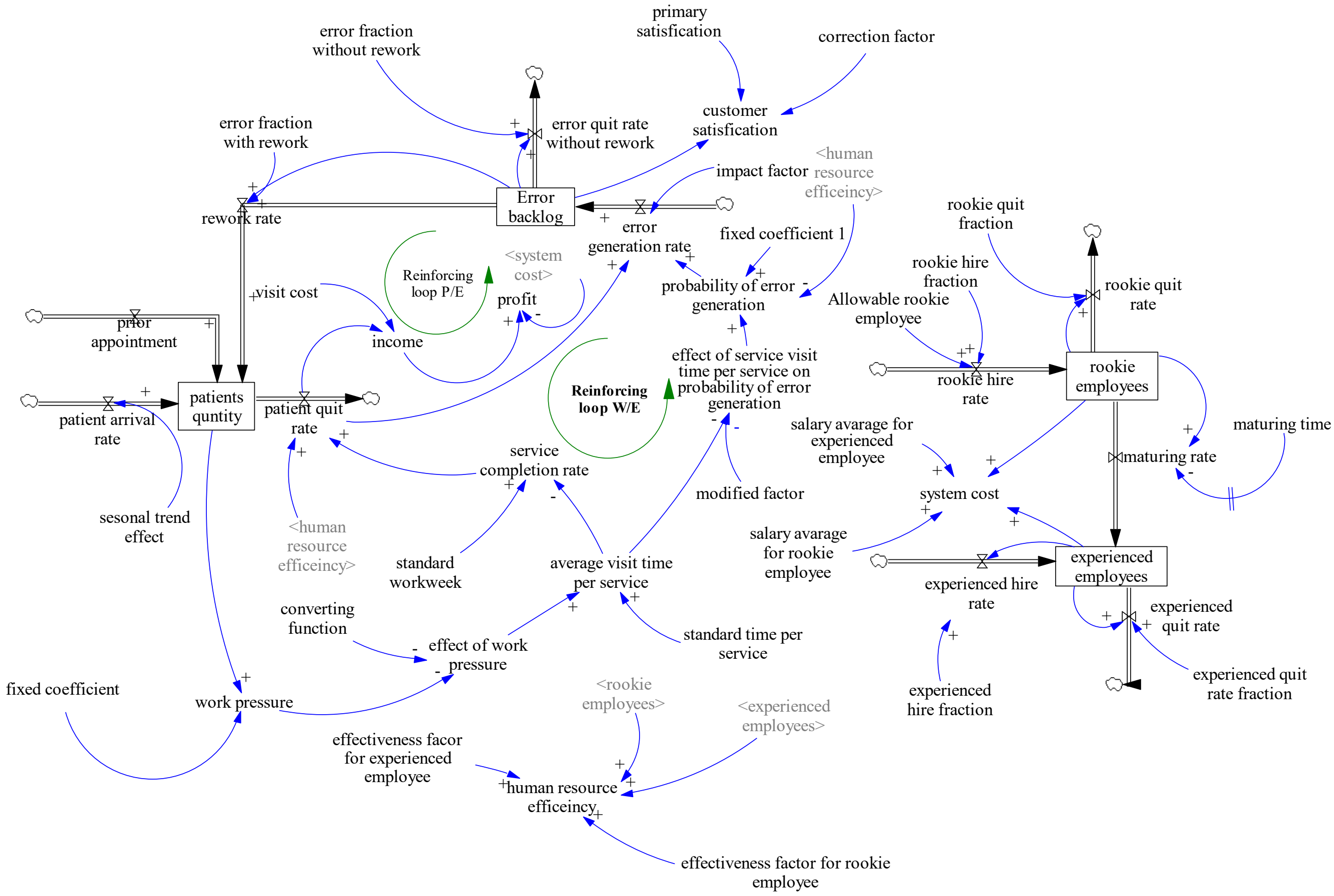

Figure 2. Stock and flow diagram

4.1.1. Human resources subsystem

The first part focuses on the human resources dynamics, as shown on the right side of Figure 2. The workforce is categorized into two groups: rookie employees and experienced employees. The total number of employees is the sum of these two groups. Over time, as rookies gain experience, they are converted into the experienced category, increasing the number of experienced employees. Both groups can quit the system, and new employees must be hired. So, the hire rate can balance rookie and experienced level variables. Efficiency levels differ between rookies and experienced employees due to their varying expertise. Consequently, an effectiveness factor is assigned to each group, and the human resource efficiency variable is determined by multiplying the number of employees by their respective efficiency rates and other related variables.

In this subsystem:

- **Rookie employees' rates** are modelled as a stock variable. Their level changes based on input (hiring) and output (quitting) rates, which employ integral operators.
- The **number of rookies** increases according to the hiring rate and decreases due to their quitting rate. After a specific period (referred to as the **maturing time**), rookies are converted into the experienced employee category. The maturing rate acts as an output for rookies and an input for experienced employees.

4.1.2. Patient quantity and error generation subsystem:

The second part of the diagram, presented on the left side of Figure 2, examines aspects related to patient quantity and error generation. This subsystem highlights the key dynamics that impact service delivery and quality. A critical factor in this model is the reduction in visit time compared to standard expectations, which, along with errors in task execution, contributes to an accumulation of errors. Rework is required to address these errors; however, not all errors are detectable or necessitate correction. The patient entry to the clinic is defined as a stock variable, with the rework rate serving as the input, patient arrival rate and prior appointment as inputs, and patient quit rate as the output. The patient quit rate is also added back to the error backlog by error generation. Error generation is introduced as an indicator of service quality erosion.

The connection between patient quantity and error generation with Human Resources subsystems occurs with the human resource efficiency variable. Because this variable is influenced by the number of rookies and experienced employees and can impact the probability of error generation. Work pressure is calculated as the ratio of patient quantity, which can influence the average visit time variable by the effect of the work pressure variable. Typically, reducing the visit time per service increases the error generation variable. Ultimately, the visit time variable can impact the probability of error generation through the effect of visit time on the service variable. The service completion rate, which can be influenced by the average visit time per service and standard workweek, can impact the patient's quit rate.

5. Validation test

Once the model is developed, its structure is validated based on expert feedback. The model's behaviour is further assessed using a sensitivity analysis, which examines how the model responds to changes in parameter values. This test is typically performed by analysing the model's sensitivity to variations in parameters. By adjusting these parameters, the consistency and logic of the model's behaviour are scrutinised and confirmed.

To validate the model, the sensitivity of work pressure to the patient arrival rate is analysed, as shown in Figure 3. In the left diagram, the model's behaviour is compared under two scenarios: increasing the patient arrival rate by 1.1 (test 1) and reducing it to 0.9 (test 2). As anticipated, work pressure and error backlog variables increase with the higher patient arrival rate and lower with the reduced patient arrival rate. Additionally, the average visit time per service variable increases with higher input (patient arrival rate) and decreases with lower one.

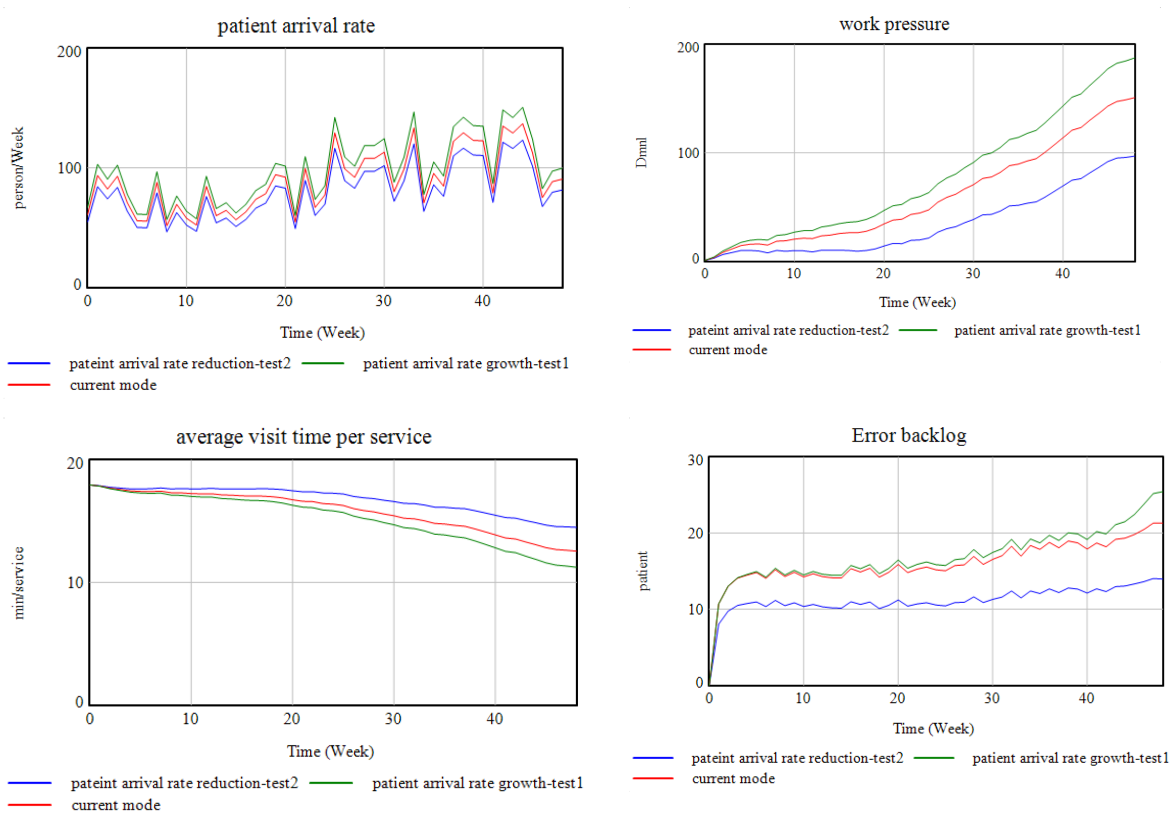

Figure 3. Validation test (patient arrival rate)

In Figure 4, the sensitivity of work pressure to human resource service is evaluated. Results are compared by reducing the rookie hire fraction to 0.5 (test-1), increasing it to 0.5 (test-1), and then increasing it by 0.9 (test-2) against the original value (0.8). As observed, increasing the fraction of rookie hires leads to a higher rookie hire rate, which in turn reduces work pressure and error backlog and increases the average visit time per service. Conversely, decreasing the rookie hire fraction leads to an increase in work pressure and error backlog, as well as a reduction in the average visit service variable.

Therefore, it can be demonstrated that our model is reliable and can be applied to subsequent analyses.

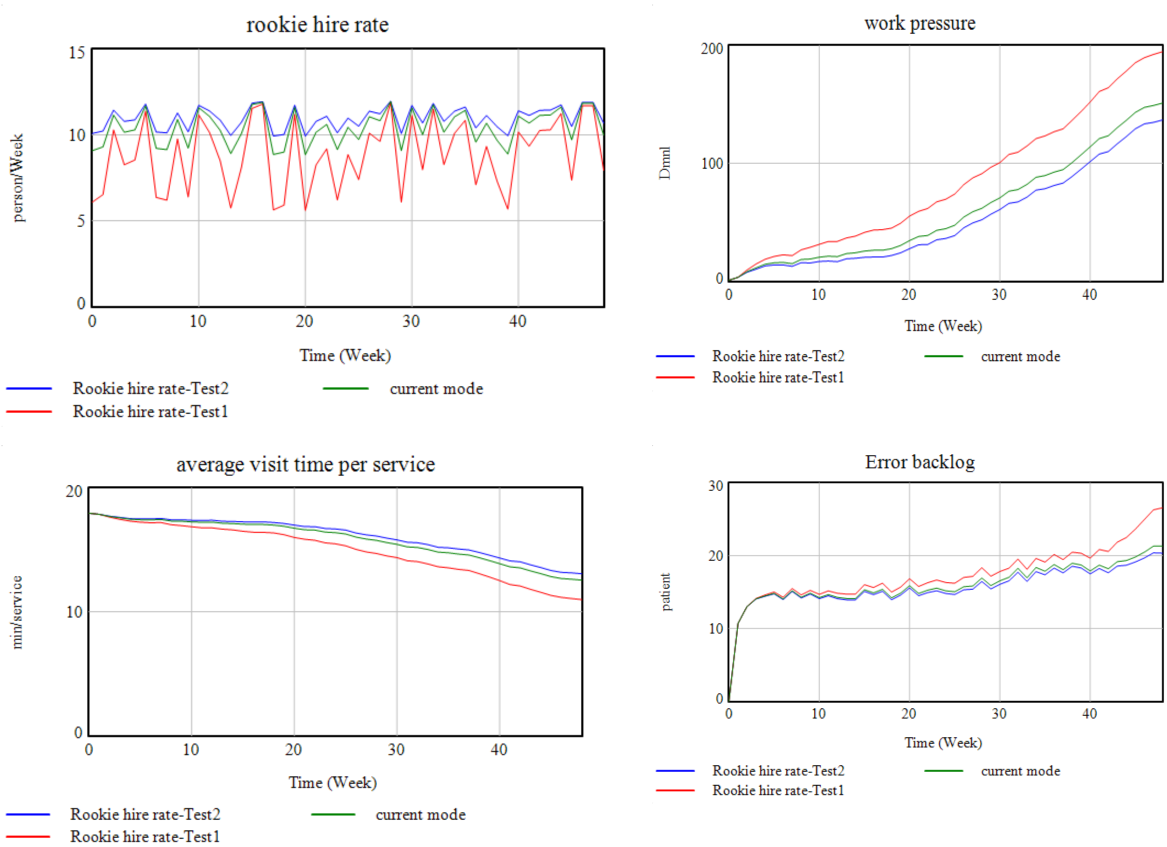

Figure 4. Validation test (rookie hire rate)

The next step after validation is simulation and model behaviour analysis based on different policies on a real-world case study described in the paper of Alizadeh-Zoeram et al., (2019), which are provided in the following sections.

6. Simulation and policy evaluation

The subsequent sections provide a detailed discussion of the three simulation models and their influence on the system behaviour.

6.1. No change in exogenous variables (Base mode)

When the primary exogenous variables such as demand (patient arrival rate) and human resources (rookie & experienced employees) are considered, external constraints like macro-level policies, cost limitations, or financial considerations may prevent any adjustments. Consequently, these variables are assumed to be the current operational state variables.

Simulation results for base mode, depicted in Figure-5.

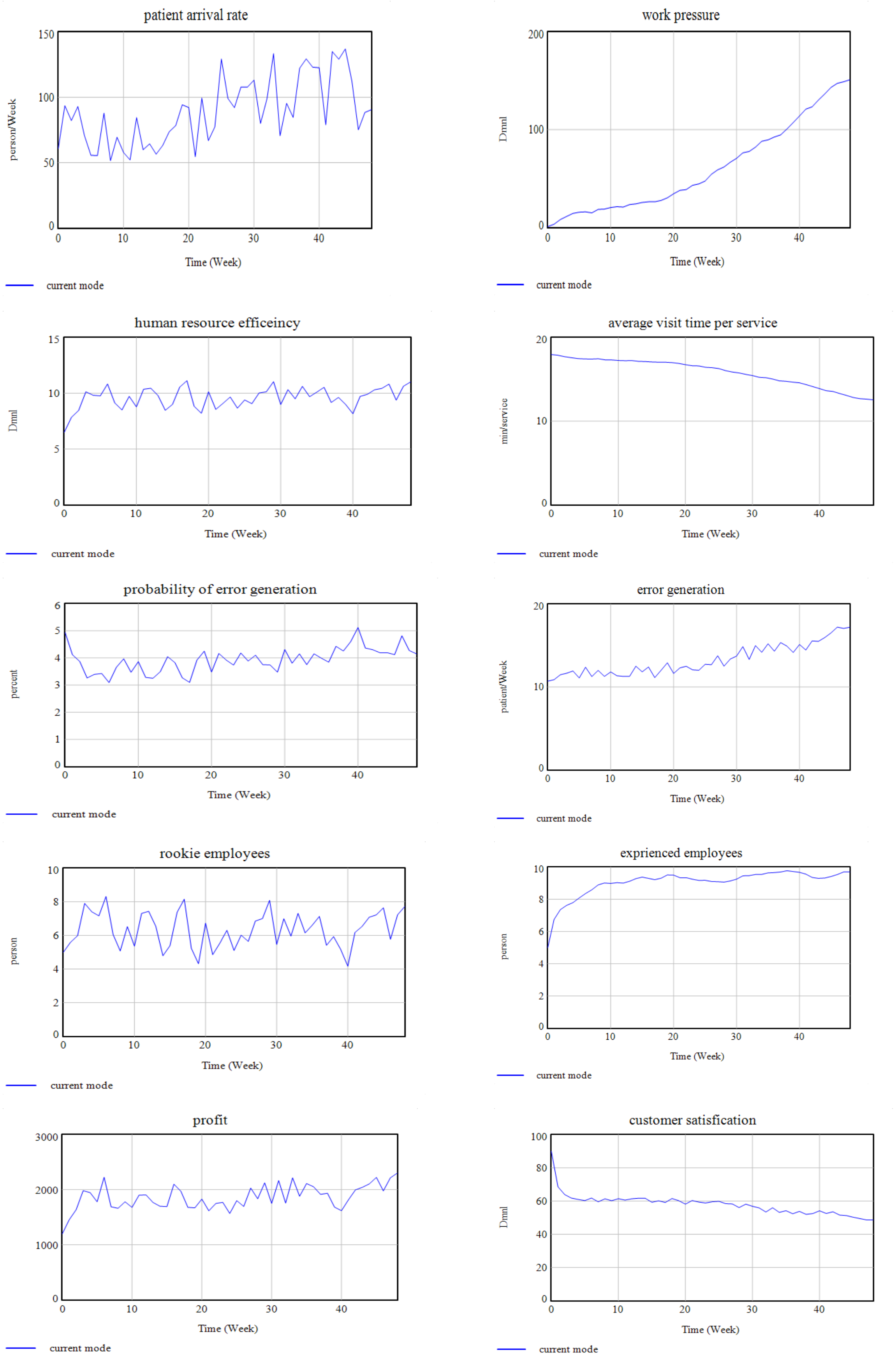

Figure 5. Simulation of base mode

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As shown in Figure 5, the patient arrival rate in the healthcare system ranges from 50 to 150 patients per week. Due to the seasonal trend effect, the number of patients increases in the second half of the year compared to the first half. Thus, work pressure increases as the number of patients grows. Under these conditions, physicians respond to the increased pressure by reducing visit times below the standard 18 minutes. Additionally, human resource efficiency, which here refers to the maximum capacity of the physicians, fluctuates around the value of 10.

Furthermore, the number of rookie employees in the clinic varies between 4 and 8 people per week due to the rate of rookie hires and the rate of quit hires. To balance work pressure, with a maturing rate that is affected by the maturing time (the time required for rookies to be converted into experienced employees) and the experienced hire rate, the value of experienced employees in the clinic increases at a moderate rate of 10 people per week. However, customer satisfaction, initially set at a base value of 100, has decreased significantly to around 55 due to increased work pressure, reduced visit times, and higher rates of visit errors. Additionally, the clinic's total profit varies around $2,000 per week, based on the patient quit rate (patients that physicians service).

With the increase in the number of patients in the second half of the year, which leads to a growth in work pressure and a reduction in visit times by physicians, the probability of error generation rises from approximately 10 to 20 per cent, and the error generation rate per week shows an upward trend.

It indicates signs of service quality decline caused by causal and feedback interactions within a dynamic system, often referred to as quality death spirals. To address these spirals, two broad strategies can be implemented. The first involves reducing the patient arrival rate, while the second focuses on increasing the number of human resources. Both approaches aim to alleviate work pressure and, consequently, reduce the rate of error generation. These strategies are elaborated in the subsequent sections.

6.2. Reducing the patient arrival rate

Reducing the patient arrival rate (i.e., limiting patient check-ins) helps lower the patient volume, resulting in reduced work pressure. The extent of reduction needed to achieve suitable work pressure can be determined through trial and error, varying patient arrival rates, and analysing simulation results. In the Base Mode, patient arrival rates vary in the range U (100, 200) - (following a uniform function)- However, in this scenario, they are converted to U (100, 110) to produce favourable outcomes. As illustrated in Figure 6, this approach significantly reduces the patient quantity and, consequently, work pressure. This reduction leads to stabilising the visit time per service variable at approximately 13 minutes, and the probability of error generation is diminished due to the reduction in work pressure.

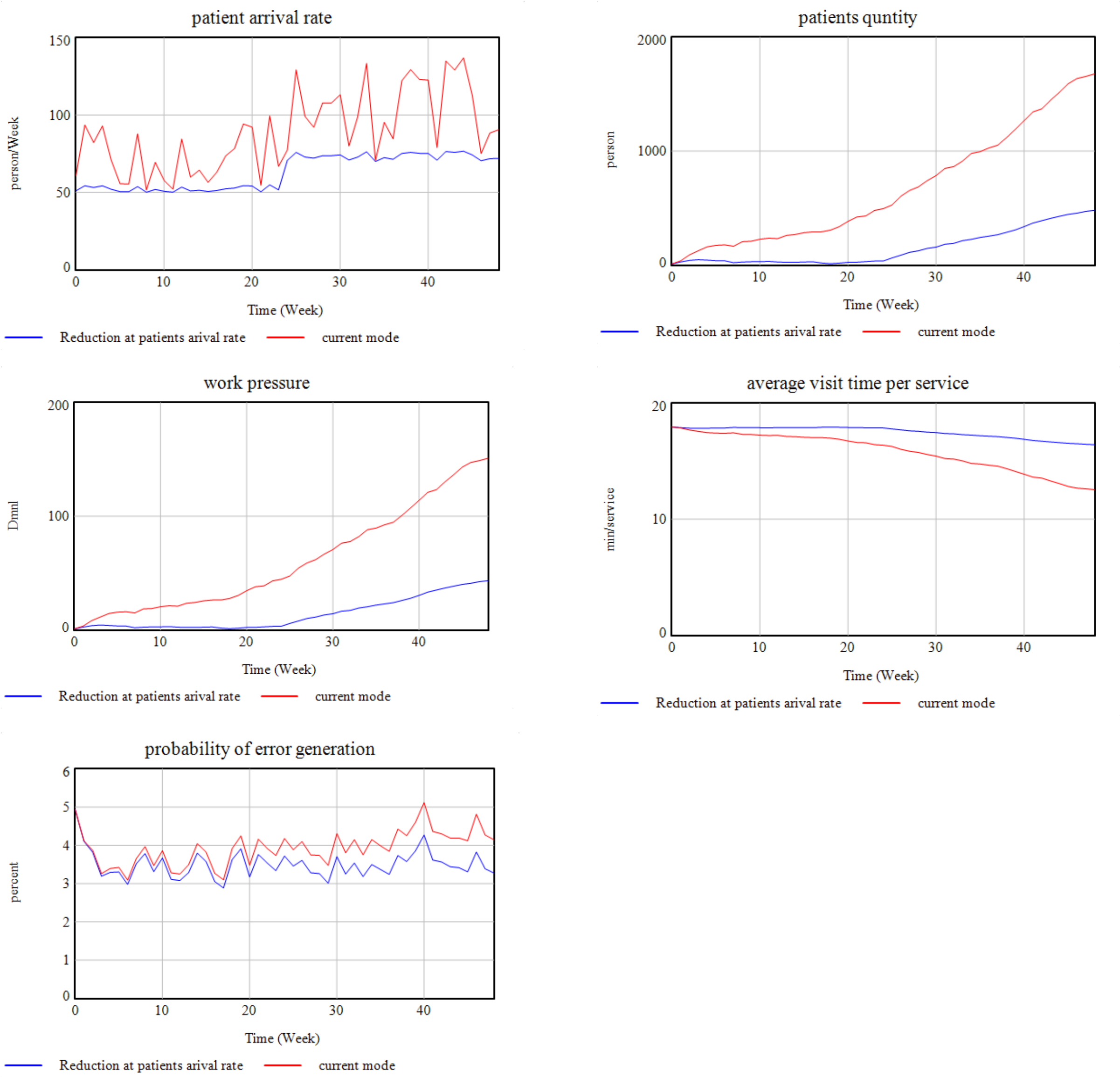

Figure 6. Reducing the patient arrival rate

Additionally, implementing this reduction in patient check-ins may conflict with broader organizational policies, making this strategy challenging to apply. Consequently, alternative measures, such as increasing human resources, may be required to address human resource efficiency shortfalls and enhance service quality. The effectiveness of this policy is examined in the next scenario.

6.3. Increasing human resources

In this scenario, we aim to boost service capacity to enhance human resource efficiency.

However, excessively increasing the number of employees can lead to underutilisation of human resources and incur unnecessary costs. Therefore, it is essential to strike a balance in increasing human resources to minimise error generation while managing system costs. As shown in Figure 7, when the fraction of experienced hires increases from 0.05 to 0.3, the number of experienced employees rises from approximately 10 to 16. Consequently, the probability of error generation decreases to around 3%. Additionally, the visit time per service variable reduces, while customer satisfaction declines in comparison with the Base Mode. In the second policy, by increasing the number of physicians, the profit variable rises to between $ 2,500 and $ 3,000 per week, representing growth compared to the current mode. Therefore, it can be a suitable policy to execute in the healthcare system.

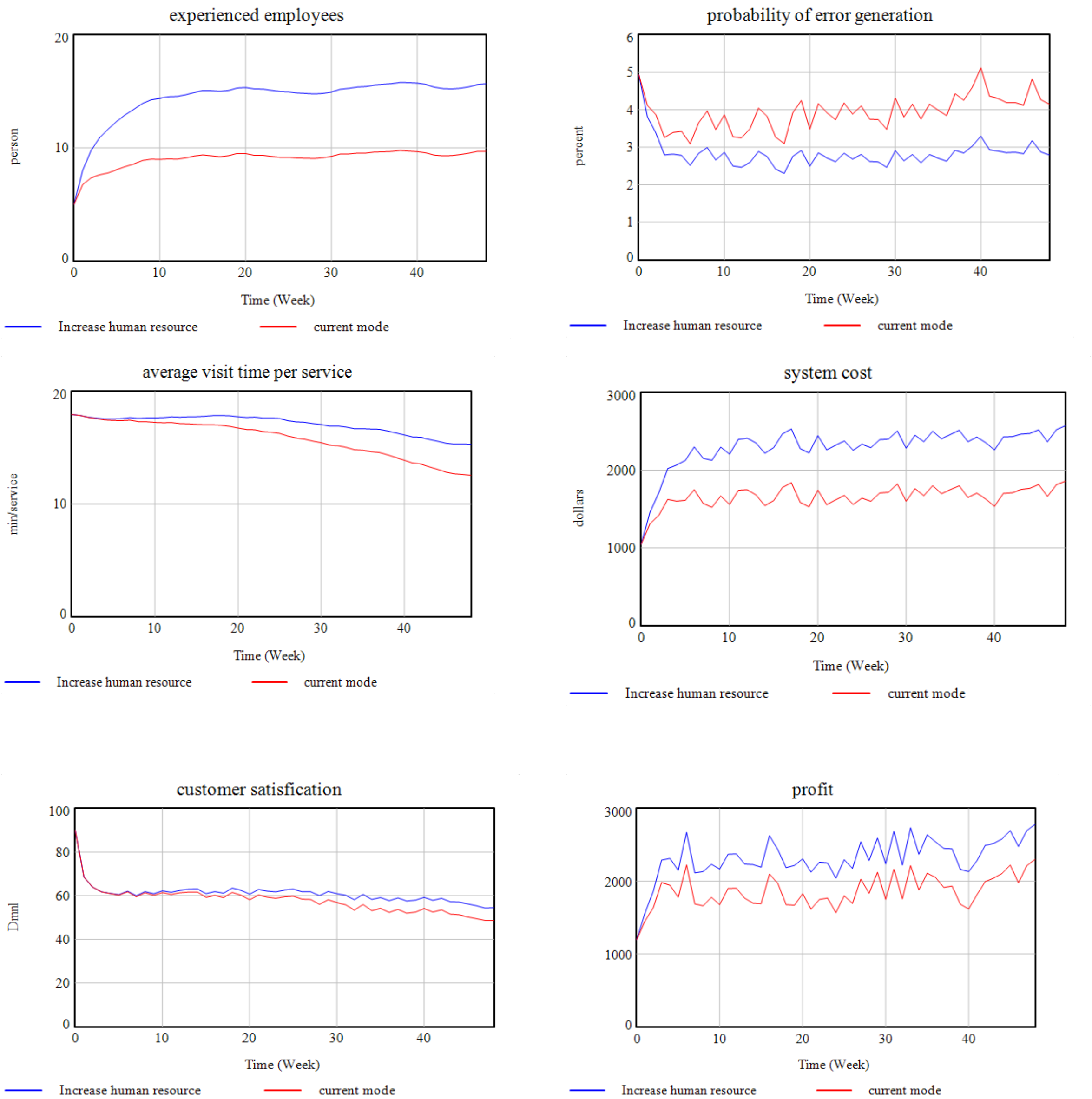

Figure 7. experienced hire fraction growth

6.4. *Increasing human resources:*

We can design an alternative scenario that appears to have better outcomes than the previous one. For this purpose, in addition to increasing the experienced hire fraction from 0.05 to 0.3, we can implement policies to reduce the experienced quit rate. To achieve this, the experienced quit rate fraction has been reduced by 0.1, and the effects of this scenario are shown in Figure 8.

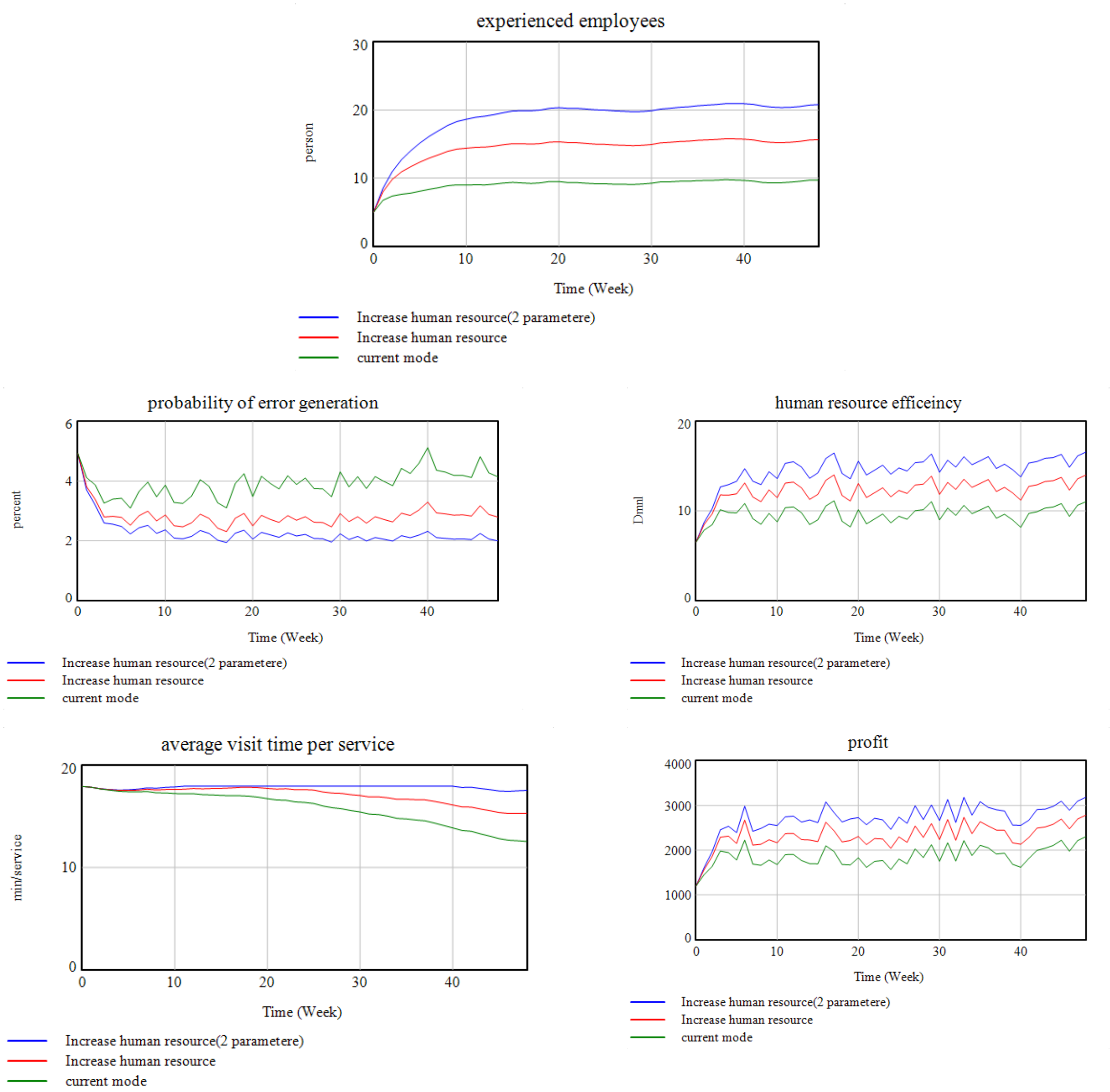

Figure 8. experienced hire fraction growth & the experienced quit rate fraction

As observed, with the increase in these two rates, the number of experienced employees in the clinic rises to approximately 20 persons. Also, the human resource efficiency has improved compared to previous scenarios, and consequently, the error probability has decreased by 2%. Additionally, the average visit time is approximately the standard time, around 17 minutes and 30 seconds. Furthermore, the clinic's profit has increased compared to previous scenarios due to improvements in human resource efficiency and a reduction in the error generation rate. These findings suggest that targeted adjustments to hiring and retention policies can effectively address service quality challenges while boosting operational outcomes.

7. Managerial insights

Efficient management of human resources and the implementation of strategic hiring and retention policies are critical for enhancing service quality and ensuring operational efficiency in healthcare systems. Given the complexities and dynamic nature of healthcare environments, achieving a balance between maintaining adequate levels of employees (physicians) and optimising levels of employees (physicians) and optimising profit is essential. These efforts not only help alleviate work pressure and reduce the likelihood of error generation but also contribute to enhancing patient satisfaction and overall system performance. The following analysis as examining patient arrival rates and modifying hiring and retention policies, to address challenges in human resource efficiency and service capacity. Some managerial insights based on numerical results are as follows:

7.1. Strategic reduction of patient arrival rates

Lowering patient arrival rates effectively reduces work pressure and stabilises visit times, as demonstrated by the reduction in patient quantity and error generation probability in this scenario.

Trial-and-error analysis and simulation modelling are essential to determine the optimal patient arrival range, ensuring system stability while balancing broader organisational policies.

However, restricting patient check-ins may conflict with overarching policies or accessibility goals for patients, making it a short-term or situational strategy rather than a universal solution.

7.2. Balancing human resource allocation

Increasing human resources addresses service capacity gaps and reduces work pressure, thereby enhancing employee efficiency and lowering the probability of error generation.

It is crucial to avoid overstaffing, which can lead to underutilization and unnecessary costs. Optimal staff allocation should strike a balance between system costs, efficiency, and quality.

As shown in the scenario, increasing the experienced hire fraction boosts the number of skilled employees, reduces error rates to approximately 3%, and contributes to improved service quality.

7.3. Retention strategies to boost efficiency

Implementing retention-focused policies, such as reducing the quit rate among experienced staff, significantly impacts service quality. As shown, lowering the quit rate leads to an increased number of experienced employees and improved workforce efficiency.

Retention strategies can reduce training costs associated with replacing experienced employees and stabilize service quality by maintaining a skilled workforce.

7.4. Improved outcomes through targeted policies

The combined strategy of increasing the proportion of experienced hires and reducing the quit rate yields the best results, with the number of experienced employees rising to 20, error probabilities decreasing by 2%, and average visit times aligning with the target of 17.5 minutes.

This dual approach also enhances the clinic's profitability, with weekly profits surpassing those of previous scenarios, emphasising the importance of integrated hiring and retention strategies.

7.5. Impact on service quality and patient satisfaction

A balanced approach to managing patient arrivals, employee efficiency, and employee levels directly influences service quality. Reduced errors and stabilized visit times contribute to improved patient satisfaction.

However, fluctuations in visit times and satisfaction in certain scenarios underscore the need for continuous monitoring and adjustments to policies to achieve sustainable improvements.

7.6. Policy recommendations

Policymakers should integrate simulation-based decision-making to test various scenarios, allowing them to evaluate the impact of changes on service capacity, costs, and quality metrics.

A holistic approach combining resource improvement, patient management, and retention strategies is essential to achieve long-term operational and quality goals in healthcare systems.

8. Conclusion

This research emphasises the crucial role of SD modelling in improving service quality within healthcare environments. By simulating various scenarios, it highlights how strategic changes in patient arrival rates, workforce allocation, and retention policies can profoundly affect service capacity, employee efficiency, visit time, error generation reduction, and patient satisfaction. The study reveals the interconnected nature of healthcare systems, where decisions can cascade, influencing work pressure, error rates, and financial outcomes. While reducing patient arrivals helps stabilise work pressure and minimise errors, this method may conflict with broader organisational objectives, necessitating alternative strategies. Enhancing human resources and optimising allocation presents a sustainable solution, balancing efficiency with organisational costs. Policies such as increasing experienced hire rates and improving employee retention enhance workforce capability, and elevate service quality. A dual strategy hiring experienced employees and reducing their quit rates—produces the best outcomes, including higher levels of experienced employees, adherence to standard visit times, lower error rates, and improved efficiency. These changes improve patient trust and satisfaction. The study underscores the value of integrating simulation-based decision-making into healthcare management. Through dynamic modelling, administrators can address challenges, optimise human resource use, and drive sustainable improvements. These findings support evidence-based policy-making, enabling healthcare systems to navigate complexities and achieve enduring excellence in patient care.

Disclosure statement

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Appendix

Formulas and Details in Stock and Flow Diagram.

Rookie Employees = INTEG (Rookie Hire Rate – Maturing Rate – Rookie Quit Rate, Initial Stock, Initial Value)	1
Rookie hire rate=rookie employees*rookie quit fraction	2
Rookie Hire Rate = Random Uniform (Allowable rookie employee*rookie hire fraction,12, 2)	3
Maturing Rate = DELAY1(rookie employees, maturing time)	4
System cost=Salary average for experienced employee*experienced employees+ rookie employees*salary average for rookie employee	5
Experienced Employees = INTEG (experienced hire rate+ maturing rate-experienced quit rate, Initial Value)	6
Experienced Hire Rate = experienced hire fraction*experienced employees	7
Experienced Quit Rate = Experienced Employees × Experienced Quit Fraction	8
Human Resources efficiency = rookie employees*effectiveness factor for experienced employee+ effectiveness factor for rookie employee*experienced employees	9
Service Completion Rate = standard workweek*fixed coefficient0/average visit time per service	10
Work Pressure = patients' quantity*fixed coefficient	11
Average visit time per service = Standard time per service*Effect of work pressure	12
Patient Quit Rate = Human resource efficiency*LN (service completion rate) *Random Uniform (13,15, 1) * a	13
Error Backlog = INTEG (error generation rate-error quit rate without rework-rework rate, Initial Value)	14
Rework Rate = Error backlog*error fraction with rework	15
Error Generation Rate = probability of error generation*(patient quit rate) *impact factor	16
Probability of Error Generation = Effect of service visit time per service on probability of error generation*fixed coefficient 1/ human resource efficiency	17
Patient arrival rate =Random Uniform (100,200,0.5) *Seasonal trend effect*0.9	18
Patients' quantity =patient arrival rate+prior appointment+rework rate-patient quit rate	19
Income = Visit cost*Patient quit rate	20
Customer satisfaction =Primary satisfaction- (Correction factor (Error backlog)	21
Seasonal trend effect =0.5+0.2*Pulse Train (24,24, 24, 50)	22
Profit= Income-b*system cost	23
Effect of service visit time per service on probability of error generation = Modified factor (Average visit time per service)	24

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