Transactions on Machine Intelligence 9(2) (2026) 142–154

ISSN Online: 2821-1693

Transactions on Machine Intelligence

Journal Homepage: https://tmachineintelligence.ir

AI-Enabled Anticipatory Capacity Planning for Smart Government: Integrating Artificial Intelligence, Strategic Foresight, and Queueing Theory under Future Demand Uncertainty

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ARTICLE INFO

Article History:
Received 9 February 2026
Received in revised form 17 April 2026
Accepted 7 May 2026
Available online 10 June 2026

Keywords:
Artificial Intelligence, AI-Enabled Capacity Planning, Strategic Foresight, Smart Government, Queueing Theory, Anticipatory Governance, Digital Resilience, Future Demand, Adaptive Capacity

ABSTRACT

The future operating environment of smart government will be increasingly influenced by artificial intelligence (AI), rapidly changing citizen expectations, demographic shifts, digital service adoption, regulatory changes, cyber disruptions, public-health emergencies, and other sources of demand uncertainty. In such an environment, conventional reactive capacity planning may be insufficient to maintain service quality and operational resilience. This study develops an AI-enabled anticipatory capacity-planning framework that integrates artificial intelligence, strategic foresight, scenario construction, and queueing theory to support resilient and adaptive smart government services. The proposed framework uses AI as an analytical and decision-support layer for identifying emerging demand patterns, supporting future-demand estimation, and translating alternative future conditions into quantitative arrival-rate assumptions. These assumptions are subsequently evaluated through an M/M/c queueing model to examine their implications for utilization, queue length, and waiting time. Three alternative capacity configurations and four future-demand scenarios are analyzed to illustrate how AI-supported foresight can be connected to quantitative service-system design. The results demonstrate a strongly nonlinear relationship between system utilization and service performance. At an arrival rate of 40 requests per hour and a service rate of 15 requests per hour per channel, increasing capacity from three to four channels reduces average waiting time from approximately 9.57 minutes to 1.14 minutes. Adding a fifth channel further reduces waiting time but results in lower capacity utilization. Scenario stress testing indicates that a four-channel system performs effectively under stable and accelerated digital adoption; however, congestion increases rapidly as demand approaches total service capacity. The findings suggest that AI should not be viewed solely as a technology for automating public services. When integrated with strategic foresight and queueing analysis, AI can contribute to anticipatory governance by supporting early identification of emerging demand pressures, detection of critical capacity thresholds, scenario-based stress testing, and adaptive resource planning. In this framework, queueing theory provides the quantitative mechanism for translating AI-supported future-demand assumptions into measurable operational consequences,

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http://dx.doi.org/10.47176/TMI.2026.252085

while strategic foresight provides the structure for dealing with uncertainty and alternative futures. The study contributes to smart government, futures studies, artificial intelligence, and operations research by proposing a transparent analytical bridge between AI-supported demand intelligence, qualitative future scenarios, and quantitative capacity planning. The framework can assist public-sector decision-makers in moving from reactive resource allocation toward anticipatory, data-informed, and adaptive capacity management.

1. INTRODUCTION

Digital transformation has become a central component of contemporary public-sector reform. Governments increasingly use integrated portals, mobile applications, cloud infrastructures, digital identity systems, automated workflows, artificial intelligence, and data analytics to improve the accessibility, speed, transparency, and quality of public services [1] to [4]. The concept of smart government extends beyond the electronic reproduction of administrative procedures. It implies a more connected, data-driven, responsive, and citizen-centered model of governance in which public institutions can coordinate information and services across organizational boundaries.

The expansion of digital government has produced important benefits, but it has also created a new category of operational vulnerability. When large numbers of citizens depend on digital platforms for tax declarations, health registration, licensing, social welfare, document verification, permits, or emergency support, service congestion becomes more than an inconvenience. Excessive delays may reduce trust, create inequality between digitally skilled and vulnerable users, interrupt legally time-sensitive transactions, and weaken confidence in state capacity. Therefore, the operational performance of digital public services should be considered part of public governance rather than a narrow technical issue.

Most public organizations still plan service capacity primarily by examining historical demand, annual budgets, current staffing, and average transaction volumes. This approach assumes that future demand will remain sufficiently similar to the past. However, the future of digital public services is unlikely to be stable or linear. Demand may be affected by demographic growth, migration, aging populations, new regulations, sudden policy deadlines, economic crises, public-health emergencies, cyber incidents, changes in citizen expectations, and the rapid diffusion of artificial intelligence. Some changes gradually increase transaction volumes, while others create abrupt peaks or shift demand from physical to digital channels. A platform designed around a single forecast may consequently perform well in ordinary periods but fail under conditions that were plausible yet insufficiently considered.

Strategic foresight provides a response to this problem. Foresight does not attempt to predict one certain future. It systematically explores alternative plausible futures, identifies drivers of change and critical uncertainties, and supports present decisions that remain effective under different conditions [5] to [8]. In the public sector, anticipatory governance refers to the institutional capacity to perceive emerging developments, interpret their implications, test policy options, and adapt before disruption becomes crisis. Yet foresight exercises often remain qualitative. They may produce compelling scenarios but do not always specify the operational capacity required to serve citizens in each future.

Operations research offers rigorous methods for service capacity analysis. Queueing theory, in particular, models systems in which requests arrive randomly, wait when service resources are occupied, receive service, and then leave the system [9] to [17]. Queueing models can estimate utilization, queue length, waiting time, and total time in the system. These indicators are highly relevant to digital public services. Nevertheless, conventional queueing applications frequently treat arrival rates as fixed values derived from present or historical data. The possible future conditions that generate those rates are rarely integrated into the model.

This paper brings these two fields together. It proposes an anticipatory capacity-planning framework in which qualitative future scenarios are translated into quantitative demand assumptions and then stress-tested through an M/M/c queueing model. The central research question is: How can strategic foresight and queueing theory be integrated to support resilient capacity planning for smart government services under uncertain future demand? The study has three objectives. First, it develops a structured bridge between scenario planning and stochastic service analysis. Second, it evaluates how alternative capacity configurations perform across different demand conditions. Third, it derives managerial and policy principles for adaptive, scalable, and resilient digital public services.

The contribution of the paper is not a new queueing formula. Its novelty lies in repositioning queueing analysis as an anticipatory governance mechanism. Instead of asking only how many service channels are required today, the proposed framework asks which configuration, reserve capacity, or scaling mechanism can remain acceptable across several plausible futures. This perspective is particularly relevant for essential digital services whose failure costs may be much higher than the cost of maintaining moderate spare capacity.

The remainder of the paper is organized as follows. Section 2 reviews the literature on smart government, strategic foresight, anticipatory governance, digital resilience, and queueing theory. Section 3 presents the integrated research framework. Section 4 describes the methodology and mathematical model. Section 5 develops future-demand scenarios. Section 6 reports the numerical results and sensitivity analysis. Section 7 discusses theoretical, managerial, and policy implications. The final section concludes the study and identifies directions for future research.

2. LITERATURE REVIEW

2.1. Smart Government and Digital Public Services

Digital government has evolved from the basic online provision of information toward integrated and increasingly intelligent public-service ecosystems. Contemporary digital transformation involves more than the adoption of new technologies; it requires the coordinated development of technological infrastructure, institutional capacity, leadership, process redesign, data governance, interoperability, and citizen engagement [1]–[4]. Accordingly, the effectiveness of a digital public service cannot be assessed merely by its online availability. It must also be evaluated in terms of accessibility, reliability, responsiveness, completion time, user experience, and its capacity to maintain acceptable performance as demand changes.

Existing research highlights the multidimensional nature of this transformation. Pedrosa et al. [1] show that evaluating digital public services increasingly requires performance indicators that connect technological capabilities with actual service outcomes. Latupeirissa et al. [2] demonstrate that digitization can improve accessibility and efficiency, although these benefits depend substantially on organizational implementation and service design. Escobar et al. [3] identify leadership, infrastructure, process alignment, stakeholder participation, and organizational readiness as important factors influencing successful public-sector digital transformation. Haug et al. [4] further show that digitally induced change extends beyond technology itself, reshaping organizational structures, professional roles, decision-making processes, and relationships between public institutions and citizens. Despite these advances, an important operational dimension remains comparatively underdeveloped in the literature. Governments may invest extensively in digital portals, cloud infrastructure, automated workflows, and intelligent services while still experiencing congestion and service delays when incoming requests accumulate faster than they can be processed. Moreover, digitalization may itself stimulate additional demand by reducing the time, cost, and effort required for citizens to access government services. Technological availability and service-processing capacity should therefore be treated as related but distinct dimensions of digital-government performance. A service platform may remain technically operational while becoming functionally congested because its processing capacity is insufficient for the volume or variability of incoming demand.

Several approaches have been proposed to improve the design and performance of digital public services. Process redesign and broader digital-transformation approaches have been identified as important mechanisms for improving public-sector service systems [18], [21]. Agile methodologies can support adaptive and iterative implementation in public-sector digital transformation [19], while process mining can help identify workflow bottlenecks and provide evidence for improving digital service delivery [20]. However, these approaches do not automatically determine the capacity required under uncertain future demand. Capacity planning requires explicit analysis of the relationship between arrival rates, service rates, the number of parallel service channels, and acceptable service standards.This operational perspective should also remain connected to the wider institutional context of digital transformation. Understanding public-sector digital transformation requires attention to how organizational definitions, expert interpretations, institutional arrangements, and implementation contexts shape transformation processes and outcomes [24]. Digital initiatives are increasingly expected not merely to modernize administrative processes but also to improve service effectiveness and the citizen experience [22]. Consequently, the performance of smart government services depends on both the quality of digital transformation and the ability of service systems to accommodate changing patterns and volumes of demand. This distinction has important implications for future-oriented capacity planning. If digital transformation changes how citizens interact with government, expands the range of available services, and lowers barriers to access, historical transaction volumes may become an insufficient basis for determining future capacity. Smart-government systems therefore require planning approaches that consider not only current operational performance but also how technological, institutional, social, and disruptive changes may reshape future demand. This requirement creates a direct connection between digital-government research and strategic foresight, which provides the basis for examining alternative future conditions rather than relying on a single extrapolation of past demand.

2.2. Strategic Foresight and Anticipatory Governance

Strategic foresight provides a systematic approach for exploring how alternative future conditions may affect present-day decisions. Rather than assuming that historical patterns will continue along a predictable trajectory, foresight examines multiple possible, plausible, and preferable futures, identifies drivers of change and emerging uncertainties, and helps decision-makers evaluate the implications of different pathways [5]–[8]. This orientation is particularly relevant to smart government, where technological innovation, regulatory change, evolving citizen expectations, demographic shifts, and disruptive events can alter both the scale and structure of demand for public services. Scenario planning is a central method within strategic foresight because it enables decision-makers to examine several internally coherent future environments rather than relying on a single expected forecast. Scenarios are not predictions; they are structured representations of how critical uncertainties and interacting drivers may produce substantially different operating conditions. Their strategic value lies in challenging assumptions, broadening organizational perspectives, and creating a structured dialogue about decisions that must remain viable under different futures [28]. This distinction becomes particularly important under conditions of deep uncertainty, in which decision-makers cannot confidently specify the probability of future states or rely on a single model of how the system will evolve [26]. In such environments, conventional optimization based on one expected future may create fragile decisions. Long-term policy analysis should instead examine how alternative strategies perform across a range of plausible conditions and identify options that remain sufficiently robust when future demand, technological conditions, or institutional constraints differ from current expectations [27].

Within government, however, foresight becomes valuable only when insights about the future are connected to present institutional choices. Anticipatory governance extends foresight from exploration to action by strengthening the capacity of public institutions to detect emerging change, interpret its implications, test policy options, coordinate responses, and adapt before pressures develop into operational failure. For smart government services, this capability is especially important because decisions concerning digital infrastructure, service architecture, staffing, automation, and processing capacity may create long-term commitments that are costly or difficult to reverse.

A persistent limitation is that foresight and scenario exercises often remain primarily qualitative. A scenario may plausibly describe accelerated digital adoption, AI-enabled service expansion, or crisis-driven demand, yet public managers still need to determine what these conditions imply for processing capacity, utilization, waiting time, and service reliability. Without an explicit mechanism for translating scenario narratives into measurable operational assumptions, foresight may provide strategic insight without sufficient guidance for budgeting, staffing, procurement, or system design.

The present study addresses this gap by linking scenario planning to quantitative capacity analysis. Drivers of change are first combined into alternative future-demand scenarios and then translated into corresponding arrival-rate assumptions. These values are not treated as forecasts or assigned probabilities; rather, they function as transparent stress-test conditions. Queueing analysis can then evaluate how alternative capacity configurations perform across these conditions, allowing decision-makers to identify where a system remains robust, where performance begins to deteriorate, and where adaptive capacity may need to be activated. In this way, strategic foresight becomes directly connected to operational decision-making while preserving its fundamental recognition that the future cannot be reduced to a single predicted outcome.

2.3. Digital Resilience and Adaptive Capacity

Resilience refers to the capacity of a system to maintain essential functions, absorb disruption, recover, and adapt. In digital public services, resilience includes technical continuity, cybersecurity, data protection, organizational coordination, workforce flexibility, and the ability to manage demand shocks. A resilient service does not necessarily avoid all disruption. It limits performance degradation, protects critical users, and restores acceptable service within a reasonable period.

Efficiency and resilience can conflict. A system designed for maximum utilization may appear cost-effective during stable periods but may have little capacity to absorb additional demand. Queueing systems are especially sensitive to this trade-off because waiting time rises nonlinearly as utilization approaches full capacity. Spare capacity, redundancy, modularity, and scalable resources may look inefficient from a static accounting perspective, yet they can be economically and socially justified when service interruption has high consequences.

Adaptive capacity provides a middle path between permanent overcapacity and fragile efficiency. Governments can combine baseline resources with temporary staff, cloud resources, automated agents, cross-trained employees, alternative channels, and demand-management mechanisms. The appropriate design depends on how rapidly additional capacity can be activated, how predictable demand is, and how costly failure would be.

2.4. Queueing Theory and Service-System Analysis

Queueing theory originated in the analysis of telephone traffic and later developed into a general framework for stochastic service systems [9] to [17]. Kendall's notation classifies models according to arrival distribution, service-time distribution, number of servers, capacity, population, and service discipline [10]. The M/M/c model assumes Poisson arrivals, exponential service times, and c parallel servers. It is analytically tractable and provides a useful first approximation for many digital service environments. More recent extensions of queueing theory have examined systems in which service rates vary with queueing conditions, highlighting that service performance may be sensitive to congestion dynamics rather than remaining fixed across all states [23].

The principal performance indicators include utilization, the probability that the system is empty, expected queue length, expected number of requests in the system, average waiting time, and average total time. Queueing theory demonstrates that high utilization can create disproportionate waiting. This relationship is frequently misunderstood in public management, where high resource utilization is sometimes interpreted as evidence of efficiency. In stochastic systems, utilization close to one may indicate vulnerability rather than optimality.

Queueing models have been applied to healthcare, telecommunications, transportation, banking, manufacturing, call centers, and cloud computing. Their application to smart government is promising because digital transactions can be represented as requests processed by human, automated, or hybrid channels. However, most studies focus on current operations. The literature contains limited integration of strategic foresight, future scenarios, and queueing-based stress testing for government services.

2.5. Research Gap and Propositions

The literature reveals three disconnected strengths. Smart-government research explains institutional and technological transformation. Foresight research explores uncertainty and multiple futures. Queueing theory quantifies service performance under stochastic demand. The gap lies at their intersection. Digital-government studies rarely translate future scenarios into operational capacity requirements; while queueing studies rarely treat demand as a scenario-dependent variable influenced by social, technological, regulatory, and crisis conditions.

This study advances two propositions. First, future-oriented capacity decisions should be evaluated across a range of plausible demand conditions rather than against a single forecast. Second, acceptable spare capacity should be viewed as a resilience investment when the social and institutional costs of digital-service failure are substantial.

3. PROPOSED FORESIGHT-DRIVEN FRAMEWORK

3.1. Framework Logic

The proposed framework integrates five stages: horizon scanning, scenario construction, scenario quantification, queueing analysis, and adaptive strategy design. Each stage transforms a different type of knowledge. Horizon scanning identifies drivers and signals. Scenario construction combines them into coherent future environments. Quantification translates scenario narratives into arrival-rate assumptions. Queueing analysis estimates performance under alternative capacity configurations. Strategy design identifies robust actions, thresholds, and contingency mechanisms.

This sequence is deliberately iterative. If queueing results show that all tested configurations fail under a plausible scenario, policymakers may redesign the service, prioritize transactions, reduce process time, or revise the scenario assumptions. Likewise, new evidence can update arrival rates, service rates, or activation times for flexible capacity.

Table 1. Structure of the foresight-driven capacity-planning framework

Stage	Core Question	Output
Horizon scanning	What developments may change future demand or capacity?	Drivers, trends, emerging issues
Scenario construction	What different service environments are plausible?	Narrative scenarios
Scenario quantification	What operational assumptions represent each scenario?	Arrival rates and service conditions
Queueing analysis	How does each capacity configuration perform?	Utilization, queue length, waiting time
Adaptive strategy design	Which actions are robust or can be triggered later?	Capacity rules and contingency plans

3.2. Drivers of Change

The demand for smart government services can be shaped by several interacting drivers. Technological drivers include digital identity, mobile access, artificial intelligence, automation, interoperability, cloud infrastructure, and cybersecurity. Social drivers include population growth, aging, migration, urbanization, digital literacy, and changing expectations. Institutional drivers include new regulations, deadlines, benefit programs, tax reforms, and administrative consolidation. Shock drivers include pandemics, natural disasters, geopolitical disruptions, infrastructure failures, and cyberattacks.

These drivers affect both demand and service capacity. Artificial intelligence may reduce processing time by automating routine decisions, but it may also increase demand because citizens can access services more easily. A cyber incident may reduce available processing capacity while simultaneously generating additional support requests. A new regulation may create a temporary surge concentrated around a legal deadline. Therefore, future scenarios should consider not only average growth but also interaction, timing, and peak intensity. Beyond isolated administrative units, smart government operates within a wider service ecosystem in which technological change, user expectations, and institutional coordination co-evolve. This perspective is consistent with Moore’s account of organizational ecosystems, where competitive and cooperative interactions shape system adaptation over time [25].

3.3. From Scenarios to Quantitative Parameters

Scenario quantification is not intended to create false precision. It provides a transparent way to connect qualitative futures with operational testing. Each scenario is represented by an arrival rate, while the service rate and number of channels can be varied to examine alternative policies. Decision-makers may derive arrival rates from historical peaks, expert judgment, trend extrapolation, simulation, or benchmark services. Ranges can also be used instead of single values.

The proposed framework distinguishes between baseline capacity and adaptive capacity. Baseline capacity is permanently available. Adaptive capacity can be activated when monitored indicators cross predefined thresholds. This distinction is important because a high-capacity configuration may be unnecessary in normal periods but essential during a demand shock.

4. METHODOLOGY AND MATHEMATICAL MODEL

4.1. Research Design

This study uses a conceptual-modeling and numerical-simulation design. It develops an integrated framework and demonstrates its application with hypothetical but realistic parameters. The purpose is not to reproduce one particular government platform, but to show how futures scenarios can be operationalized through queueing analysis. Such illustrative modeling is appropriate when access to administrative transaction data is restricted by privacy, security, or institutional constraints.

Calculations were implemented in Python 3.11 and verified using standard M/M/c equations. The numerical experiment examines three capacity configurations under a baseline arrival rate and then performs a sensitivity analysis across four future-demand scenarios.

4.2. System Description and Assumptions

Citizen requests enter a digital platform and are processed by parallel service channels. A channel may represent an employee, an automated workflow, an artificial intelligence module, a computing resource, or an integrated human-machine unit. If all channels are busy, incoming requests join a common queue. Completed requests leave the system.

The model assumes that arrivals follow a Poisson process with average rate lambda, service times are exponentially distributed with mean service rate mu per channel, c identical channels operate in parallel, service follows a first-in-first-out discipline, waiting space is unlimited, the calling population is effectively infinite, and parameters remain constant during the evaluated period. Although these assumptions simplify reality, they provide a clear benchmark for capacity analysis [13] to [17].

4.3. M/M/c Formulation

System utilization: rho = lambda/(c mu), where rho < 1
Probability of an empty system: P0 = [sum from n=0 to c-1 of ((lambda/mu)^n/n!) + ((lambda/mu)^c/(c!(1-rho)))]^-1
Average queue length: Lq = [P0(lambda/mu)^c rho]/[c!(1-rho)^2]
Average waiting time in queue: Wq = Lq/lambda
Average time in the system: W = Wq + 1/mu
Average number in the system: L = Lq + lambda/mu

Little's Law, L = lambda W and Lq = lambda Wq, is used as a consistency check [15]. A steady-state solution requires lambda < c mu. If this condition is violated, the system cannot process requests as quickly as they arrive and the expected queue grows without bound.

4.4. Decision Objective

The conventional objective is to minimize waiting time or total cost. A foresight-oriented objective must also consider resilience. A general decision function can be written as Z(c) = alpha Wq(c) + beta C(c) + gamma R(c), where C(c) is the cost of capacity, R(c) is the expected loss associated with service failure or noncompliance, and alpha, beta, and gamma represent policy priorities. Because reliable cost and failure-loss data are not available in the illustrative case, the numerical analysis focuses on waiting time, queue length, and utilization.

The decision is therefore not simply to select the configuration with the lowest waiting time. It is to identify a configuration or adaptive rule that provides an acceptable balance between ordinary efficiency and future resilience.

5. FUTURE-DEMAND SCENARIOS

5.1. Scenario Construction

Four scenarios are used to demonstrate how plausible futures can be translated into queueing parameters. They are not predictions. They represent distinct operational conditions that a smart government platform may need to withstand. The service rate is set at 15 requests per hour per channel. Arrival rates range from 30 to 55 requests per hour.

Table 2. Future-demand scenarios used in the numerical analysis

Scenario	Description	Arrival Rate (requests/hour)	Primary Driver
S1 Stable Digital Growth	Gradual adoption with predictable transaction volumes	30	Incremental digitization
S2 Accelerated Adoption	Rapid migration from physical to digital channels	40	Policy and user adoption
S3 AI-Enabled Expansion	New intelligent services stimulate more frequent interactions	50	AI and service expansion
S4 Demand Shock	Crisis, deadline, cyber disruption, or emergency creates a concentrated peak	55	Discontinuity or shock

5.2. Scenario Narratives

Scenario S1 represents a future of stable digital growth. Government gradually expands online services, citizen adoption increases predictably, and no major disruption occurs. Existing planning methods remain broadly effective, although continuous monitoring is still necessary.

Scenario S2 represents accelerated adoption. New digital-by-default policies, improved mobile access, and integration of public portals shift a larger share of transactions online. Demand increases materially, but the change remains manageable if capacity planning is timely.

Scenario S3 represents AI-enabled expansion. Intelligent assistants, automated eligibility checks, proactive notifications, and personalized services make interaction with government easier and more frequent. Artificial intelligence improves productivity, but the number of requests also rises. This scenario illustrates why automation does not automatically eliminate congestion.

Scenario S4 represents a demand shock. A legal deadline, emergency benefit, public-health event, cyber incident, or sudden closure of physical offices produces a sharp concentration of requests. The scenario tests resilience rather than ordinary efficiency. It is especially relevant for essential services where delayed access can create social or legal harm.

6. RESULTS AND ANALYSIS

6.1. Baseline Capacity Comparison

The baseline comparison uses an arrival rate of 40 requests per hour and a service rate of 15 requests per hour per channel. Three, four, and five-channel configurations are evaluated.

Table 3. Performance of alternative capacity configurations

Channels	Utilization	Average Queue Length	Waiting Time (hours)	Waiting Time (minutes)	Total Time (hours)
3	0.889	6.380	0.1595	9.57	0.2262
4	0.667	0.757	0.0189	1.14	0.0856
5	0.533	0.185	0.0046	0.28	0.0713

The three-channel configuration operates at 88.9 percent utilization. Although this appears efficient, the average waiting time is approximately 9.57 minutes and the expected queue length is 6.38 requests. More importantly, the system has little reserve capacity and is vulnerable to relatively small increases in demand.

Adding a fourth channel reduces utilization to 66.7 percent and average waiting time to approximately 1.14 minutes. The reduction in waiting time is about 88 percent. This large improvement illustrates the nonlinear behavior of queues and the strategic value of a moderate capacity buffer.

The five-channel configuration reduces average waiting time to approximately 0.28 minutes, but utilization falls to 53.3 percent. The fifth channel therefore creates additional resilience and may be justified for critical services, yet its marginal benefit during ordinary conditions is smaller than the benefit created by the fourth channel.

6.2. Scenario Stress Test

The stress test fixes capacity at four channels and evaluates performance across the four future-demand scenarios.

Table 4. Scenario Stress Test Results for a Four-Channel Service System

Scenario	Arrival Rate	Utilization	Average Queue Length	Waiting Time (minutes)	Interpretation
S1	30	0.500	0.174	0.35	Strong reserve capacity
S2	40	0.667	0.757	1.14	Balanced performance
S3	50	0.833	3.289	3.95	Congestion warning
S4	55	0.917	9.039	9.86	High vulnerability

The four-channel system performs comfortably under S1 and remains effective under S2. In S3, utilization increases to 83.3 percent and average waiting time rises to 3.95 minutes. Performance is still operationally feasible, but the system enters a warning zone in which further demand increases produce rapid deterioration.

Under S4, utilization reaches 91.7 percent and average waiting time increases to 9.86 minutes. Compared with S1, demand rises by 83 percent, but waiting time increases by more than twenty-seven times. This result demonstrates why linear extrapolation is dangerous. A service platform may appear stable until utilization crosses a critical threshold, after which performance degrades quickly.

The results suggest that utilization should be monitored as an anticipatory indicator. In the illustrative system, a threshold near 80 percent could trigger additional resources. The exact threshold should be determined empirically for each service because acceptable waiting time, arrival variability, service heterogeneity, and failure consequences differ.

6.3. Adaptive Capacity Test

A purely static choice between four and five channels is not the only policy option. A more flexible design could maintain four permanent channels and activate a fifth channel when utilization or predicted demand exceeds a threshold. The fifth channel could be an automated processing module, cross-trained staff, temporary cloud capacity, or a shared service unit.

Under S3, a fifth channel would reduce utilization from 83.3 percent to 66.7 percent and sharply reduce waiting. Under S4, five channels would produce utilization of 73.3 percent, moving the system away from the congestion region. This suggests that scalable capacity is particularly valuable when high-demand periods are intermittent rather than permanent.

Activation time is crucial. Flexible capacity that requires several weeks to procure may not protect a service from a sudden shock. Anticipatory planning should therefore specify not only how much capacity is needed but also how quickly it can become operational.

7. DISCUSSION

7.1. Theoretical Contribution

The paper contributes to the literature by combining three analytical traditions that are usually treated separately. Smart-government research provides the institutional context, strategic foresight provides alternative future conditions, and queueing theory provides measurable operational consequences. The framework shows how scenario narratives can become model inputs without reducing foresight to a single forecast.

The approach also expands the role of queueing theory. Classical queueing analysis is often retrospective or operational: observed demand is used to optimize current resources. In the proposed framework, arrival rates are scenario variables. Queueing analysis becomes a method of testing preparedness across futures. This shift supports anticipatory governance because it reveals vulnerability before actual congestion occurs.

A further contribution concerns the meaning of efficiency. High utilization is not always efficient when demand is uncertain and service failure is costly. From a dynamic perspective, moderate spare capacity can create option value. It allows the organization to absorb peaks, maintain service standards, and avoid emergency interventions.

7.2. Managerial Implications

Managers should connect service-level indicators with strategic planning. Waiting time, backlog, and utilization should not remain confined to technical dashboards. They should inform staffing, budgeting, cloud procurement, automation, and continuity planning. Each major digital service should have explicit performance targets and a documented response when indicators approach critical levels.

Capacity planning should use ranges and scenarios rather than one annual estimate. A baseline forecast can be supplemented by accelerated-adoption and shock conditions. Managers can then identify which resources must be permanent, which can be shared, and which can be activated temporarily.

Automation should be evaluated on both sides of the queue. It may increase the service rate, but it may also increase the arrival rate by making transactions easier and creating new forms of contact. The net effect should be tested rather than assumed.

7.3. Policy Implications

First, governments should establish a demand-foresight process for critical digital services. Horizon scanning and scenario review can be conducted annually or when major policy and technology changes occur. Second, service-level standards should include maximum acceptable waiting, backlog, and recovery time. Third, capacity triggers should be defined in advance so that additional resources can be activated before service failure.

Fourth, digital resilience should be recognized in public budgeting. Spare or scalable capacity may appear unnecessary when evaluated only against average demand. Its value becomes visible when the cost of failure, public dissatisfaction, legal delay, and emergency intervention are considered. Fifth, public organizations should conduct regular stress tests, including scenarios in which demand increases while part of the normal capacity is unavailable.

Finally, foresight units, digital-government agencies, operations managers, and cybersecurity teams should collaborate. Future demand, technical availability, and institutional continuity are interdependent. Fragmented planning can produce a platform that is technologically sophisticated but operationally fragile.

7.4. Limitations

The study uses hypothetical parameters and a classical M/M/c model. Real platforms may experience bursty arrivals, non-exponential service times, priority classes, abandoned requests, repeated submissions, multi-stage workflows, and dependencies between services. The model also assumes constant parameters during each evaluated period.

The scenarios are illustrative and do not represent probabilities. Their purpose is to demonstrate the integration of foresight and queueing analysis. Empirical applications should construct scenarios with relevant stakeholders and use administrative data to estimate parameter ranges. Cost, equity, cybersecurity, and service criticality should also be incorporated into future extensions.

8. CONCLUSION

Smart government services operate in an environment of increasing uncertainty. Historical averages alone are insufficient for capacity planning when digital adoption, artificial intelligence, demographic change, regulation, and crises can alter demand rapidly. This paper proposed an anticipatory capacity-planning framework that integrates strategic foresight with queueing theory.

The numerical analysis showed that service performance deteriorates nonlinearly as utilization approaches total capacity. At the baseline demand level, moving from three to four channels generated a major reduction in waiting time, while a fifth channel provided additional resilience with lower ordinary utilization. Scenario testing demonstrated that the four-channel system remained effective under stable and accelerated adoption but became vulnerable under AI-enabled expansion and demand shock conditions.

The central policy lesson is that capacity should not be designed only for today's average demand. Governments should combine baseline resources with scalable capacity, thresholds, and contingency plans. Queueing indicators can serve as early-warning signals when they are embedded in a wider foresight and governance process.

The proposed framework transforms queueing theory from a narrow operational tool into an instrument of anticipatory governance. It enables policymakers to connect plausible futures with present decisions, identify fragile configurations before failure occurs, and design digital public services that are not only efficient but also adaptive, resilient, and citizen-centered.

Future research should validate the framework with empirical transaction data, compare alternative queueing models, incorporate priority and abandonment, and combine scenario planning with discrete-event simulation, robust optimization, machine learning, and real-time forecasting. Comparative applications across sectors and countries could further clarify how institutional context affects the relationship between future demand, capacity, and digital resilience.

Declaration

We acknowledge that we used ChatGPT to enhance the academic writing of our manuscript while ensuring the originality and integrity of our work.

Transparency Statement

The data supporting this study are available upon reasonable request to the corresponding author, subject to ethical and confidentiality considerations.

Acknowledgments

We would like to express our gratitude to all individuals who contributed to this project.

Declaration of Interest

The authors declare that they have no competing interests.

Funding

This research received no specific grant from any funding agency, commercial, or not-for-profit sectors.

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