A Survey of Dual-layer Principal-Agent Model and Payment Reform in Healthcare Economics

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Abstract

This survey critically examines the dual-layer principal-agent model in healthcare economics, focusing on the role of Diagnosis-Related Groups (DRG) and Dynamic Incentive Programs (DIP) in payment reform. By transitioning from traditional fee-for-service models to prospective payment systems, DRG frameworks have significantly improved hospital efficiency and expenditure management, particularly in countries like China and South Korea. However, challenges such as upcoding and classification inaccuracies necessitate continuous refinement and regulatory oversight. Technological advancements, including machine learning models like DRG-LLaMA and KG-MTT-BERT, enhance DRG classification accuracy, supporting precise performance evaluations and resource management. DIP complements these efforts by aligning financial incentives with provider performance, fostering innovative practices and advanced technologies to optimize care delivery. The integration of self-supervised learning models exemplifies technological enhancements under DIP, refining diagnostic processes and improving patient outcomes. The dual-layer principal-agent model offers a robust framework for understanding stakeholder interactions, emphasizing the need for aligned incentives and innovative payment mechanisms. Future research should focus on refining these models, exploring long-term impacts, and addressing regulatory challenges to improve healthcare quality and financial sustainability. By leveraging advanced technologies and data-driven approaches, healthcare systems can evolve to deliver high-quality, cost-effective care tailored to diverse patient needs.

1 Introduction

1.1 Purpose and Relevance of the Survey

This survey critically evaluates the dual-layer principal-agent model in healthcare economics, focusing on the transformative effects of payment reform mechanisms such as Diagnosis-Related Groups (DRG) and Dynamic Incentive Programs (DIP). It explores the construction and functionality of the DRG system to enhance understanding of its impacts, particularly concerning flat-rate payment systems [1]. In China, the shift from traditional fee-for-service models to prospective payment systems represents a significant policy transition aimed at addressing inefficiencies and rising costs associated with fee-for-service structures, as highlighted by the advocacy for a DRG-based case-mix payment system in public hospitals [2, 3]. Additionally, the survey examines the influence of DIP payment reforms on inpatient care metrics, including total hospital costs and Length of Stay (LOS) across various patient demographics [4].

The relevance of this survey lies in its potential to inform policy decisions through a comprehensive assessment of contemporary payment reform strategies and their implications for cost-effectiveness and efficiency in healthcare delivery. By analyzing DRG systems across different countries, the survey addresses existing knowledge gaps and offers insights into global best practices [5]. Integrating findings from multiple studies contributes to a deeper understanding of how incentive mechanisms

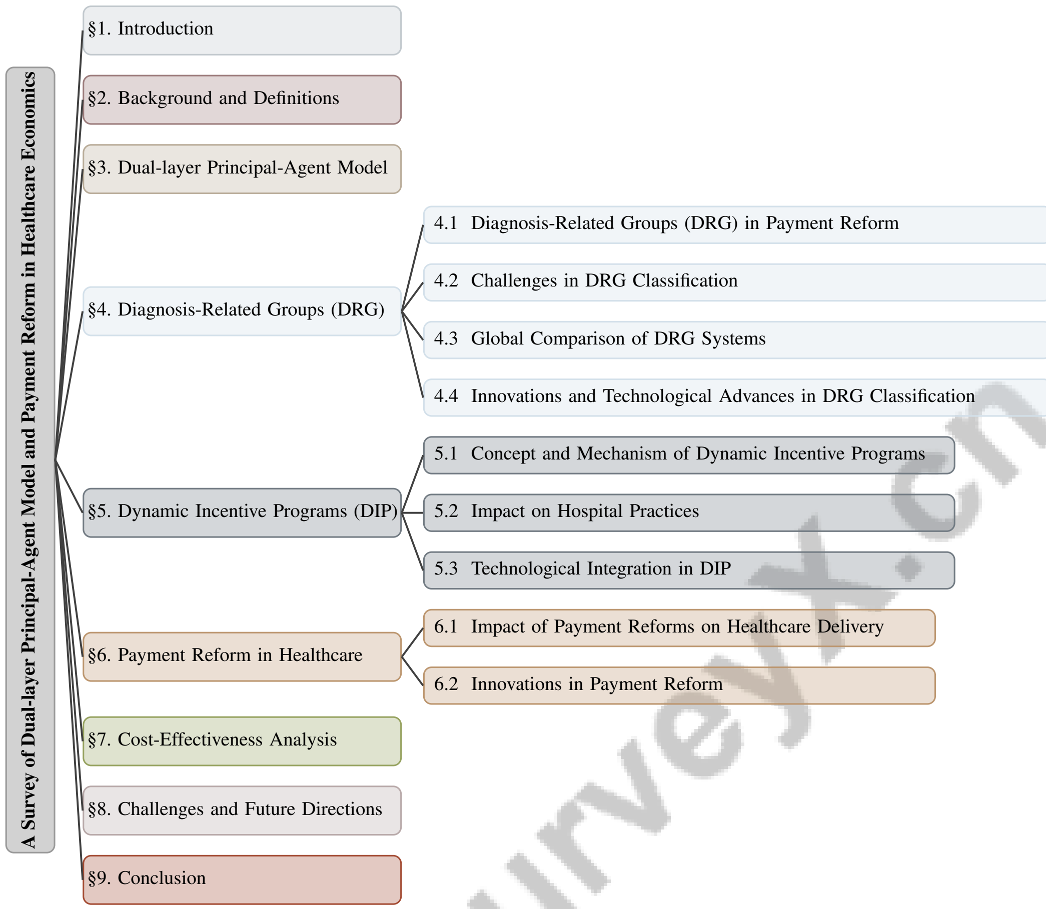

Figure 1: chapter structure

can be structured to optimize healthcare outcomes and financial sustainability, particularly in light of evolving healthcare needs and the increasing emphasis on cost-effective public health solutions.

1.2 Structure of the Survey

This survey is systematically organized to explore the complexities of the dual-layer principal-agent model and its implications for payment reform in healthcare economics. Following the introduction, it provides a comprehensive overview of the principal-agent model and key terminologies, such as DRG and DIP, establishing a foundation for an in-depth analysis of the model's conceptual framework and the intricate interactions among stakeholders in healthcare delivery. This analysis is particularly pertinent given recent changes in reimbursement structures, such as the 2007 Medicare DRG restructuring, which incentivized hospitals to adjust coding practices, potentially leading to upcoding that affects both public and private payers. By examining these dynamics, the survey elucidates how managerial workarounds and payment reforms, like the Diagnosis-Intervention Packet system, influence cost management and healthcare efficiency across various systems [6, 4, 7, 8].

Subsequently, the survey investigates the role of DRG in payment reform, detailing its implementation, classification challenges, and global comparisons to assess its effectiveness across healthcare systems [3]. The discussion then transitions to Dynamic Incentive Programs (DIP), examining their concepts, impacts on hospital practices, and the integration of technology to enhance effectiveness.

The analysis proceeds to examine payment reform strategies, evaluating their effects on healthcare delivery and cost management, alongside recent innovations in this field. A section on cost-effectiveness analysis evaluates payment reforms through various metrics and case studies, including the APR-DRG ROM model.

Finally, the survey addresses challenges and future directions in implementing these models and reforms, considering regulatory and systemic hurdles while suggesting areas for future research to enhance model effectiveness. The conclusion synthesizes key findings regarding payment reforms, such as DRG restructuring and the DIP system, highlighting their implications for hospital behavior, including tendencies to upcode patient diagnoses for increased reimbursements. It reflects on how these models affect healthcare economics by influencing hospital costs, length of stay, and overall care delivery efficiency, thus underscoring the need for ongoing refinements to payment structures to mitigate challenges like diagnostic ambiguity and ensure equitable patient treatment across different insurance groups [6, 4].The following sections are organized as shown in Figure 1.

2 Background and Definitions

2.1 Overview of Principal-Agent Model in Healthcare

The principal-agent model is integral to healthcare economics, delineating the interactions between hospitals (agents) and payers such as insurance entities or government bodies (principals). It provides a framework for understanding reimbursement structures and payment reforms aimed at boosting efficiency and cost management [5]. Delegating decision-making from principals to agents introduces complexities like information asymmetry and potential conflicts of interest.

In healthcare, this model supports the implementation of Diagnosis-Related Groups (DRG) and Dynamic Incentive Programs (DIP). The DRG system, originating in the United States, is pivotal for assessing hospital productivity and standardizing performance metrics, significantly impacting expenditure management and performance across various systems, including Brazil [5]. Despite its widespread adoption, the DRG system faces criticism, notably in Germany, over its ability to ensure equitable, high-quality healthcare [1]. China's transition to a DRG-based payment model marks a major policy shift aimed at improving hospital efficiency and cost control [2].

Dynamic Incentive Programs (DIP) further illustrate the principal-agent model's dynamic nature, reforming provider-patient interactions through innovative payment strategies [4]. These strategies align agent incentives with principal objectives, fostering cost-effective, high-quality healthcare. Thus, the principal-agent model offers a robust framework for analyzing stakeholder interactions and incentives, underscoring the need for structured mechanisms to mitigate information asymmetry and align interests.

2.2 Key Terms and Definitions

Diagnosis-Related Groups (DRG) are essential in healthcare payment systems, classifying hospital cases by similar clinical characteristics and resource use. The DRG framework aids in pricing, insurance payments, and performance evaluation [2]. Malaysia's MY-DRG® Casemix System exemplifies DRG principles' adaptability to local contexts, demonstrating its flexibility across national settings [9]. However, implementing DRG systems in developing countries is challenging due to limited data and research on outcomes [5].

Dynamic Incentive Programs (DIP) offer innovative healthcare payment reforms, focusing on aligning financial incentives with provider and payer goals. China's adoption of DIP, influenced by the DRG system, highlights dynamic incentive mechanisms' role in enhancing healthcare efficiency and quality [4]. These mechanisms address principal-agent model issues by reducing information asymmetry and aligning stakeholder incentives, promoting cost-effective, high-quality healthcare delivery.

The integration of advanced technologies in healthcare, though promising, faces challenges such as reliance on large annotated datasets for supervised learning, which can be impractical and hinder generalization across diverse imaging scenarios [10]. Understanding these key terms and their implications is crucial for grasping the complexities of payment reforms and dynamic interactions within healthcare systems.

In recent years, the dual-layer principal-agent model has emerged as a significant framework for understanding healthcare delivery dynamics. This model not only delineates the relationships between various stakeholders but also provides insights into the mechanisms that govern these interactions. As illustrated in Figure 2, the hierarchical structure of this model is divided into two distinct layers: the upper layer emphasizes payer-provider relationships, while the lower layer focuses on provider-patient interactions. This figure effectively highlights the conceptual framework of the model, showcasing core elements such as Diagnosis-Related Groups (DRG) and Dynamic Incentive Programs (DIP). Furthermore, it underscores the role of technological advancements in enhancing communication among stakeholders and optimizing resource allocation. By integrating these elements, the dual-layer principal-agent model offers a comprehensive understanding of the complexities inherent in healthcare delivery.

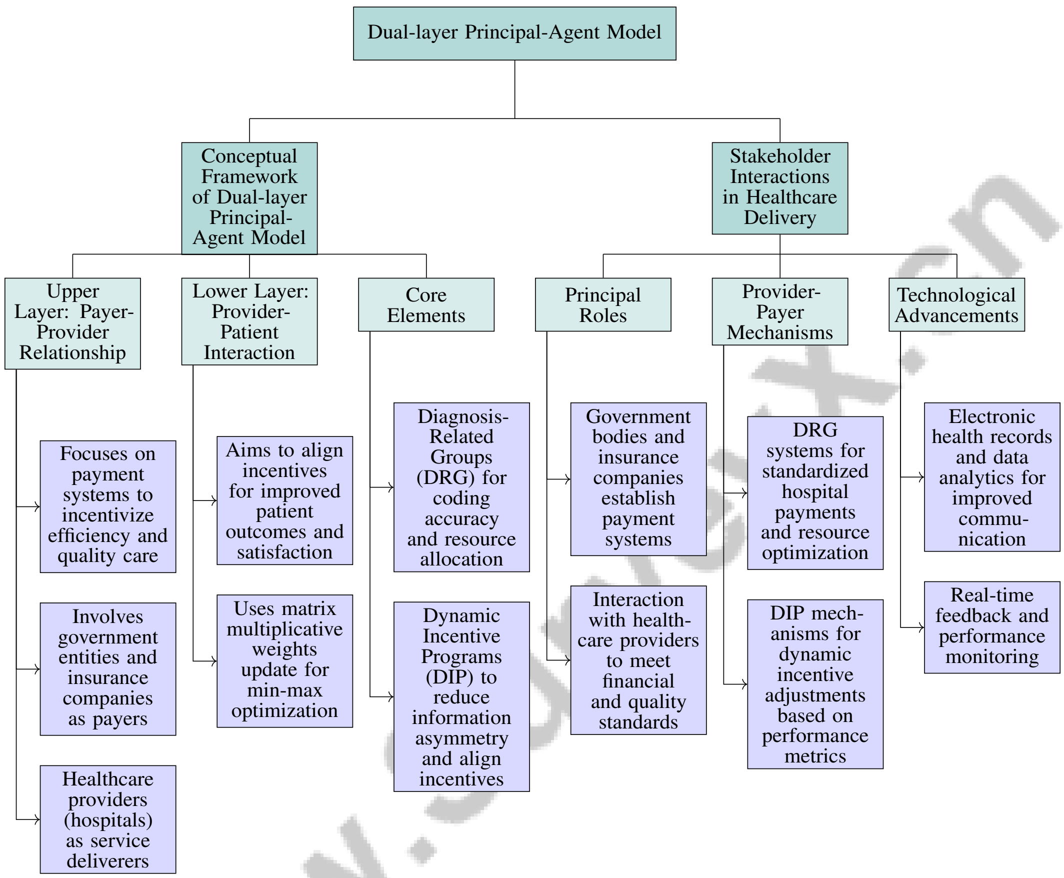

Figure 2: This figure illustrates the hierarchical structure of the dual-layer principal-agent model in healthcare delivery, highlighting the conceptual framework and stakeholder interactions. The model is divided into an upper layer focusing on payer-provider relationships and a lower layer addressing provider-patient interactions. Core elements such as Diagnosis-Related Groups (DRG) and Dynamic Incentive Programs (DIP) are emphasized, alongside technological advancements enhancing stakeholder communication and resource allocation.

3 Dual-layer Principal-Agent Model

3.1 Conceptual Framework of Dual-layer Principal-Agent Model

The dual-layer principal-agent model advances healthcare economics by incorporating a complex framework that reflects the multifaceted dynamics among stakeholders such as government entities, insurance firms, hospitals, and patients. This model extends the traditional principal-agent framework by integrating system dynamics modeling (SDM), agent-based modeling (ABM), and discrete event simulation (DES) to simulate the intricate interactions and feedback loops in healthcare delivery [11]. The upper layer of this model focuses on the relationship between payers (government or insurance companies) and healthcare providers (hospitals), emphasizing payment systems that incentivize efficiency and quality care. The lower layer addresses provider-patient interactions, aiming to align incentives to improve patient outcomes and satisfaction, using methods like the matrix multiplicative weights update for navigating min-max optimization [12].

Central to this model is the Diagnosis-Related Groups (DRG) system, which is vital for coding accuracy and resource allocation within hospitals [9]. The DRG framework categorizes healthcare cases, facilitating efficient resource management and supporting the dual-layer model's objectives. Complementarily, Dynamic Incentive Programs (DIP) highlight stakeholder interactions, aiming to reduce information asymmetry and align incentives across the healthcare system [4]. By examining research on DRG themes such as efficiency, cost management, and healthcare outcomes, the dual-layer principal-agent model underlines the importance of systematic reviews to assess its efficacy across different contexts [5]. This model provides a robust foundation for understanding incentives and decision-making processes, offering insights into developing payment reforms that enhance cost-effectiveness and care quality [3].

3.2 Stakeholder Interactions in Healthcare Delivery

The dual-layer principal-agent model elucidates stakeholder roles and interactions within healthcare systems, focusing on incentive alignment to optimize delivery. Principals, typically government bodies and insurance companies, establish payment systems and regulations, interacting with healthcare providers (hospitals and clinics) who deliver care while meeting financial and quality standards [5]. Providers must also align incentives with patient outcomes to ensure high-quality, cost-effective care. Mechanisms such as Diagnosis-Related Groups (DRG) and Dynamic Incentive Programs (DIP) are integral to reducing information asymmetry and aligning interests across stakeholders [4].

As illustrated in Figure 3, the hierarchical structure of stakeholder interactions in healthcare delivery emphasizes the dual-layer principal-agent model, payment mechanisms, and technological advancements. The principal-agent model highlights the importance of incentive alignment and payment systems, while the payment mechanisms underscore the roles of DRG systems and DIP reforms. Furthermore, technological advancements, including electronic health records (EHR) and data analytics, enhance communication and performance monitoring, thereby improving stakeholder interactions.

DRG systems standardize hospital payments based on case mix, encouraging resource optimization and efficiency, relying on accurate coding and classification [9]. DIP mechanisms innovate payment reforms by dynamically adjusting incentives based on performance metrics, promoting continuous improvement in healthcare delivery [4]. These technologies support the model's objective of aligning stakeholder incentives by providing real-time feedback and performance monitoring, fostering a collaborative environment conducive to achieving healthcare goals.

The dual-layer principal-agent model provides a comprehensive framework for understanding complex stakeholder interactions in healthcare delivery. By emphasizing financial incentive alignment and innovative payment mechanisms, it offers essential insights for developing strategies to improve delivery efficiency and service quality. Recent reforms, such as the DRG system and Diagnosis-Intervention Packet (DIP) payment model, aim to manage costs and incentivize appropriate care through differential reimbursement structures. However, challenges like upcoding and diagnostic ambiguity necessitate ongoing refinement of payment systems to optimize outcomes [6, 8, 4].

4 Diagnosis-Related Groups (DRG)

4.1 Diagnosis-Related Groups (DRG) in Payment Reform

Diagnosis-Related Groups (DRG) systems have revolutionized healthcare payment reform by shifting from traditional fee-for-service (FFS) models to prospective payment systems, thereby controlling hospital expenditures and enhancing efficiency. DRGs classify hospital cases into groups with similar clinical characteristics and resource utilization, aligning financial incentives with clinical outcomes and promoting cost-effective healthcare delivery [3, 13].

As illustrated in Figure 4, which highlights the key aspects of DRGs in payment reform, these systems demonstrate adaptability and effectiveness across the globe. For instance, Malaysia's MY-DRG system underscores the financial impact of coding errors, highlighting the importance of accurate DRG classification [9]. In the U.S., DRG-based inpatient payment systems face challenges with manual coding, demanding improvements in prediction accuracy and efficiency. Innovations such as machine learning algorithms and knowledge graphs, exemplified by the KG-MTT-BERT model, enhance DRG classification accuracy by integrating medical knowledge with advanced textual

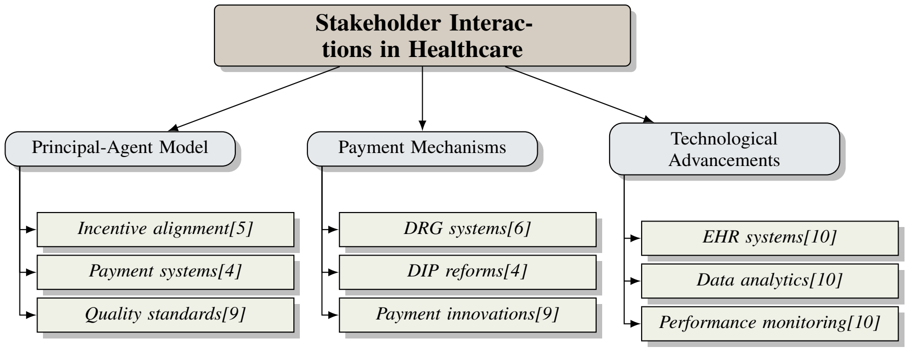

Figure 3: This figure illustrates the hierarchical structure of stakeholder interactions in healthcare delivery, focusing on the dual-layer principal-agent model, payment mechanisms, and technological advancements. The principal-agent model emphasizes incentive alignment and payment systems, while payment mechanisms highlight DRG systems and DIP reforms. Technological advancements include EHR systems and data analytics, enhancing communication and performance monitoring.

processing [14]. Additionally, frameworks for detecting missing diagnoses improve medical record accuracy and DRG enrollment, mitigating cost losses from missed diagnoses [15].

Despite these advancements, challenges like upcoding and downcoding persist, affecting equitable resource distribution. Accurate data recording and classification are essential to maintain DRG system integrity [16]. The application of DRG systems in developed countries has led to improved hospital efficiency and cost management, showcasing the system's potential as a benchmark for evaluating hospital productivity [5].

The DRG system's significance in payment reform is evident in its capacity to standardize hospital payments, enhance transparency, and promote efficient resource use. By aligning financial incentives with healthcare outcomes, DRG systems play a crucial role in shaping sustainable healthcare practices globally, as evidenced by their widespread adoption and pilot programs. The restructuring of DRG systems, such as Medicare's 2007 expansion to account for complications, illustrates their potential to influence hospital behavior and reimbursement strategies [6, 16, 13, 8].

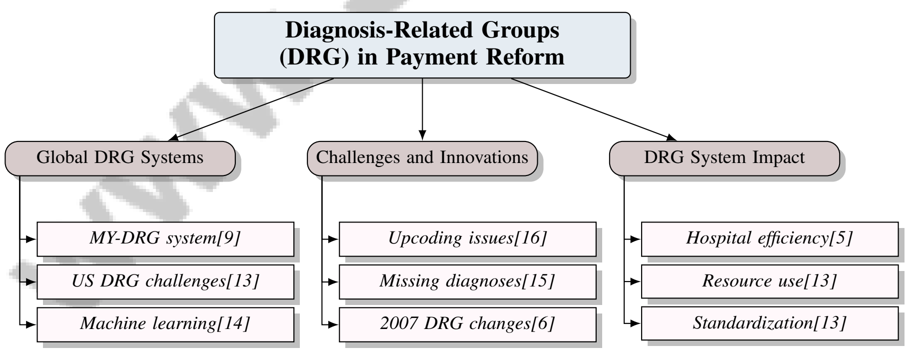

Figure 4: This figure illustrates the key aspects of Diagnosis-Related Groups (DRG) in payment reform, highlighting global systems, challenges, innovations, and the impact on hospital efficiency and resource use.

4.2 Challenges in DRG Classification

Diagnosis-Related Groups (DRG) classification faces significant challenges that impact its effectiveness and equity. Variability in DRG systems across countries necessitates adaptability to local healthcare contexts while maintaining consistency in grouping, coding, and payment mechanisms [13]. This variability complicates DRG implementation, particularly in regions with entrenched FFS models and disparities in healthcare funding [3].

A critical challenge is the complexity of DRG prediction, a multi-class classification task distinct from the multi-label classification of ICD coding, rendering existing methods inadequate for accurate DRG assignment [17]. Manual coding's labor-intensive nature exacerbates this issue, with a study indicating coding errors in 89.4% of selected patient medical records [9]. Existing benchmarks struggle with DRG assignments, particularly in managing multi-class classification tasks necessary for accurate predictions [18]. The reliance on manual detection introduces inefficiencies and challenges in maintaining accuracy, especially in complex medical environments [15]. Additionally, the APR-DRG system, incorporating subclasses like Risk of Mortality (ROM) and Severity of Illness (SOI), has not been extensively validated as a predictor of perioperative mortality, revealing gaps in current benchmarks [19].

Addressing challenges related to missing diagnoses, data manipulation, and the complexity of medical text is crucial for enhancing DRG systems' accuracy and fairness. Leveraging advanced technologies such as natural language processing and machine learning can improve the detection of missed diagnoses, ensure reliable data classification, and facilitate equitable healthcare reimbursement practices [20, 16, 14, 15]. Developing sophisticated algorithms and data processing techniques supports the overarching goals of payment reform and healthcare efficiency.

4.3 Global Comparison of DRG Systems

Diagnosis-Related Groups (DRG) systems' implementation and effectiveness vary significantly among the 49 countries that have adopted them and the 13 countries currently piloting these systems. Differences in healthcare priorities, economic conditions, and socio-political factors shape each country's DRG framework, influencing design and operational strategies. Patient demographics, disease mix, and data quality impact the classification of patient treatment episodes and resource consumption patterns [13, 3]. High-income countries are moving away from DRG as the primary payment method, seeking more nuanced models to accommodate complex healthcare needs and improve patient outcomes.

Conversely, middle-income countries increasingly adopt DRG systems as part of healthcare reforms to enhance efficiency and control costs. For instance, various DRG systems in China exhibit distinct structural variations impacting hospital management and patient care differently [2]. This strategic transition from traditional FFS models to prospective payment systems is perceived as more sustainable and effective in managing healthcare resources.

DRG systems' effectiveness differs between developed and developing nations. Developed countries typically achieve higher efficiency and better healthcare outcomes with DRG systems, attributed to advanced healthcare infrastructures and robust data management capabilities [5]. In contrast, developing countries face challenges in adapting DRG systems due to limitations in data availability, coding accuracy, and resource allocation, hindering improvements in healthcare delivery and cost management.

The global comparison of DRG systems underscores the necessity of adapting these frameworks to align with local healthcare characteristics and needs, as evidenced by diverse implementation strategies and managerial adaptations across various countries. This adaptation is critical for ensuring DRG systems effectively address local healthcare challenges, optimize resource allocation, and improve patient outcomes [13, 3, 20, 8]. While DRG systems provide a framework for standardizing payments and enhancing transparency, their success largely depends on addressing each country's unique challenges and needs.

4.4 Innovations and Technological Advances in DRG Classification

Advancements in Diagnosis-Related Groups (DRG) classification have been propelled by machine learning technologies and data-driven methodologies, enhancing healthcare payment systems' precision and efficiency. These innovations transition from traditional expert-oriented grouping methods, criticized for opacity and high costs, to more transparent, adaptive data-based approaches. Machine learning algorithms replicate expert systems' decision-making processes, allowing continuous updates at lower costs. Recent studies show data-based DRG grouping achieves strong classification performance, significantly enhancing accuracy in new DRG systems, addressing complexities in patient treatment episodes, and supporting effective financial management and resource allocation [3, 20].

The DRG-LLaMA model, leveraging Low-Rank Adaptation (LoRA) with a substantial dataset, surpasses existing benchmarks like ClinicalBERT and CAML by optimizing performance on clinical data, improving DRG assignments' precision. The KG-MTT-BERT model integrates domain-specific medical knowledge through a knowledge graph, overcoming standard BERT model limitations by enhancing multi-type medical texts handling, essential for accurate DRG classification [14]. The shift from expert-driven to data-driven approaches allows continuous updates based on real or simulated cases, creating a more dynamic and responsive DRG classification system [20].

Managerial workarounds have been conceptualized as a novel improvement, offering systematic analyses of methods healthcare managers use to navigate DRG systems, aiding in understanding practical challenges and opportunities within DRG implementation [8]. Additionally, a more detailed classification system enables hospitals to code patients more favorably, potentially increasing reimbursements and addressing downcoding issues [16].

Localized adaptations, such as the Brazilian DRG system benchmark, provide relevant comparisons and productivity assessments, emphasizing the importance of contextualizing DRG systems to local healthcare environments [21]. Studies comparing mandatory and voluntary participation hospitals have tested DRG payment systems' effects on patient care outcomes, offering insights into DRG implementation's varying impacts across different institutional contexts [22].

Future research should focus on integrating DRG systems with value-based purchasing methods, enhancing flexibility, and exploring DRGs' coexistence with other payment mechanisms. This integration is essential for adapting DRG systems to evolving healthcare payment reforms [13]. These innovations and technological advances underscore DRG classification systems' ongoing evolution, aiming to improve healthcare delivery and financial sustainability.

5 Dynamic Incentive Programs (DIP)

5.1 Concept and Mechanism of Dynamic Incentive Programs

Dynamic Incentive Programs (DIP) represent a transformative shift in healthcare payment systems, aligning financial incentives with provider performance to enhance efficiency and cost management. At the core of DIP is the dynamic adjustment of payment mechanisms based on performance metrics, prompting providers to optimize care delivery and resource utilization [4]. This approach addresses the limitations of static payment systems, which often neglect patient variability and healthcare outcomes.

As illustrated in Figure 5, the key components and challenges of Dynamic Incentive Programs in healthcare are highlighted, showcasing core mechanisms, technological integrations, and areas for improvement. DIP mechanisms involve comprehensive evaluation frameworks that benchmark hospital performance, influencing reimbursement rates and resource allocation [6]. Continuous monitoring of these metrics allows healthcare systems to adapt to changing demands, fostering ongoing improvement and innovation. Advanced data processing techniques are crucial for accurate performance assessment. For example, integrating natural language processing (NLP) within frameworks like DRG-LLaMA enhances the prediction of Diagnosis-Related Groups (DRGs) from clinical notes, improving performance evaluations [17]. Additionally, self-supervised learning models have been employed for tasks such as PET image denoising, showcasing the application of cutting-edge technologies in healthcare data analysis [10].

DIP mechanisms often utilize parallel approximation methods, including matrix multiplicative weights updates, to address complex optimization challenges in healthcare delivery [12]. These methods enable efficient computation of solutions, allowing for adaptive payment strategies that reflect real-time performance outcomes. The restructuring of Medicare's DRG system in 2007 aimed to create differential reimbursement based on patient severity, leading to unintended consequences like upcoding to maximize reimbursements. These findings underscore the need for sophisticated data analytics to optimize financial incentives, ensuring equitable healthcare delivery while controlling costs [6, 7]. By aligning provider incentives with patient outcomes, DIP fosters sustainable and efficient healthcare environments, improving healthcare delivery and financial sustainability.

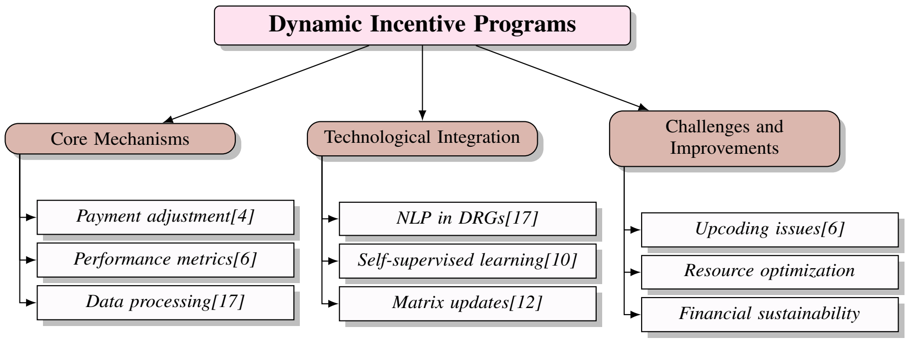

Figure 5: This figure illustrates the key components and challenges of Dynamic Incentive Programs in healthcare, highlighting core mechanisms, technological integrations, and areas for improvement.

5.2 Impact on Hospital Practices

Dynamic Incentive Programs (DIP) significantly influence hospital practices by restructuring financial incentives that guide healthcare delivery. Programs like the Diagnosis Related Group (DRG) system encourage hospitals to enhance operational efficiency and improve patient care quality. The 2007 restructuring of the DRG system by Medicare introduced differential reimbursement based on patient severity, incentivizing accurate coding of patient conditions. However, this has raised concerns over upcoding, where hospitals may misclassify patients to secure higher reimbursements. Similarly, countries like China, with their Diagnosis-Intervention Packet (DIP) payment system, face challenges such as increased costs and longer patient stays, underscoring the need for ongoing refinement of these incentive structures [6, 16, 8, 4].

DIP promotes the adoption of advanced technologies and data-driven approaches that enhance decision-making and operational efficiency. Self-supervised pre-training models exemplify the technological advancements facilitated by DIP, significantly improving healthcare data processing capabilities. In medical imaging, such models have achieved state-of-the-art denoising results, preserving spatial details and quantification accuracy [10]. These enhancements enable hospitals to refine diagnostic processes and treatment plans, leading to more accurate and efficient patient care.

Furthermore, DIP encourages hospitals to implement innovative practices that streamline operations and reduce unnecessary expenditures. By dynamically adjusting reimbursement rates based on performance metrics, DIP incentivizes hospitals to optimize resource utilization, minimize waste, and improve care coordination. This approach enhances care quality by encouraging accurate patient classification and supports the financial sustainability of healthcare institutions by aligning reimbursement structures with care complexity, reducing upcoding risks, and ensuring efficient resource allocation [16, 3, 8, 6, 4].

DIP's impact on hospital practices is also reflected in the focus on continuous performance evaluation and improvement. Utilizing sophisticated data analytics and machine learning methodologies enables hospitals to enhance operational efficiency and patient outcomes. Advanced models, such as KG-MTT-BERT, can effectively classify medical texts, while data-driven methods for DRG classification streamline reimbursement processes, reduce costs, and improve accuracy. By continuously updating these systems with real-world data, hospitals can align better with evolving healthcare standards and reimbursement structures, ultimately enhancing patient care and operational transparency [6, 14, 20, 15]. This data-driven approach fosters a culture of continuous improvement, motivating hospitals to enhance practices and achieve better healthcare outcomes.

Dynamic Incentive Programs are crucial in transforming hospital practices by aligning financial incentives with efficiency and quality care goals. By leveraging advanced technologies and data-driven strategies, the DIP payment system assists hospitals in enhancing operational efficiency and improving healthcare service quality. This integration addresses rising healthcare costs and varying patient group challenges, ultimately leading to better outcomes for patients and providers. Moreover, implementing the DIP system highlights the need for ongoing improvements to mitigate issues like upcoding and diagnostic ambiguity, ensuring a more effective healthcare delivery framework [4, 6, 16, 8].

5.3 Technological Integration in DIP

The integration of advanced technologies within Dynamic Incentive Programs (DIP) enhances their effectiveness by enabling precise performance evaluations and facilitating adaptive payment mechanisms. Machine learning and data analytics play a pivotal role in refining assessments of healthcare providers' performance, aligning incentives closely with healthcare outcomes [17]. NLP frameworks facilitate the extraction and analysis of complex clinical data, improving the accuracy of DRG classification and subsequent evaluations [18].

Self-supervised learning models have shown significant potential in advancing healthcare data processing. In medical imaging, these models enhance PET image denoising, preserving critical spatial details and quantification accuracy essential for diagnosis and treatment planning [10]. Leveraging such technologies allows DIP to support hospitals in optimizing clinical workflows and improving patient outcomes.

Parallel approximation methods, such as matrix multiplicative weights updates, further contribute to the technological enhancement of DIP by efficiently addressing complex optimization challenges in healthcare delivery [12]. These methods enable dynamic adjustments of payment systems, ensuring they reflect real-time performance metrics and healthcare demands.

The technological integration within Dynamic Incentive Programs underscores the critical role of data-driven methodologies in transforming healthcare payment systems. The impact of DRG restructuring on hospital reimbursement practices highlights the potential for both upcoding and downcoding, which can significantly affect financial allocations among providers [6, 16, 7]. By aligning provider incentives with patient outcomes through advanced technologies, DIP fosters a more efficient and sustainable healthcare environment, ultimately contributing to improved healthcare delivery and financial sustainability.

6 Payment Reform in Healthcare

6.1 Impact of Payment Reforms on Healthcare Delivery

Payment reforms, notably through Diagnosis-Related Groups (DRG) and Dynamic Incentive Programs (DIP), have notably reshaped healthcare delivery. In China, transitioning from fee-for-service to DRG-based payments has effectively managed costs and improved hospital efficiency [2]. Similarly, South Korea's mandatory DRG implementation has reduced Length of Stay (LOS) and readmission rates across various diseases [22]. However, these systems also face challenges like systematic upcoding, as seen in the U.S., where the MS-DRG system has led to increased reimbursement claims without corresponding care improvements [6]. France experienced similar issues with DRG classification changes in 2009, particularly among for-profit hospitals [16]. These challenges underscore the need for robust regulations to ensure DRG systems achieve their intended goals.

Navigating DRG systems involves complexities such as managerial workarounds to manage costs and policy conflicts while maintaining efficiency [8]. Studies of Brazilian hospitals reveal lower productivity in clinical DRGs compared to American counterparts, highlighting the need for better management practices [21]. Technological advancements, like the DRG-LLaMA model, enhance DRG prediction accuracy, impacting coding and resource allocation [18]. Automated solutions for the write-missing diagnoses problem further improve coding accuracy and hospital revenue.

DIP's impact on healthcare delivery is significant, resulting in increased total costs and LOS, indicating major transformations [4]. Continuous validation and refinement of payment reforms are crucial, as shown by the potential of validating APR-DRG subclasses to enhance surgical risk prediction, thereby improving patient outcomes [19]. The implementation of DRG and DIP systems has reshaped healthcare delivery by enhancing efficiency and managing costs. China's National Healthcare Security Administration initiated DIP reforms to control rising expenses, although challenges like upcoding persist. In the U.S., the 2007 DRG restructuring introduced differential reimbursements based on case severity, incentivizing higher patient acuity reporting. These reforms highlight the need for ongoing refinement to address challenges while optimizing healthcare delivery across diverse patient groups [4, 6, 8]. Regulatory oversight and technological integration are essential to tackle issues like upcoding and ensure high-quality, cost-effective care.

6.2 Innovations in Payment Reform

Recent innovations in payment reform strategies focus on enhancing transparency and cost-effectiveness, particularly through advancements in DRG classification and DIP. The data-based grouping method offers improved transparency and cost-effectiveness over traditional DRG methods, facilitating accurate and equitable resource allocation [20]. This approach optimizes hospital operations and financial management.

Advanced technologies, such as the KG-MTT-BERT model, have revolutionized payment reform strategies by improving DRG prediction accuracy. This model utilizes a knowledge graph to enhance processing of multi-type medical texts, refining DRG classification [14]. Future research aims to further refine this model and explore its application in resource management within healthcare settings, potentially integrating DRG predictions with hospital resource allocation models to enhance efficiency and reduce costs.

Machine learning and natural language processing (NLP) have significantly improved the precision of performance evaluations and resource allocation in healthcare payment systems. These technologies facilitate flexible reimbursement models that align financial incentives with patient health outcomes, promoting a more efficient and sustainable healthcare system. By leveraging mechanisms such as DRGs, which adjust payments based on patient condition severity, healthcare providers are encouraged to deliver appropriate care while minimizing unnecessary services. This alignment incentivizes accurate patient condition reporting, enhancing budget allocations and supporting the overall goal of improving healthcare quality and cost-effectiveness [6, 16, 14, 8].

These innovations emphasize the critical role of technology and data-driven approaches in transforming healthcare systems. By improving the accuracy and transparency of payment mechanisms, such as DRG and DIP systems, these advancements enhance healthcare delivery and promote financial sustainability. This dual benefit arises as hospitals are incentivized to document patient severity accurately, ensuring appropriate reimbursements and minimizing practices like upcoding that can distort financial allocations. Ultimately, these improvements foster a more equitable healthcare environment that supports both providers and patients through better resource management and care quality [13, 16, 8, 6, 4].

7 Cost-Effectiveness Analysis

7.1 Metrics for Evaluation

Benchmark	Size	Domain	Task Format	Metric
DIP[4]	229,306	Healthcare Economics	Cost Analysis	Total Costs, LOS
MS-DRG[6]	7,000,000	Health Economics	Upcoding Detection	DRG Weight Increase
DRG[22]	3,038,006	Health Economics	Comparative Analysis	LOS, Total Medical Costs
DRG-Brasil[21]	145,710	Hospital Management	Productivity Evaluation	Median Length of Stay, Productivity Ratio
MY-DRG[9]	464	Clinical Coding	Coding Error Analysis	Coding Error Rate, Potential Revenue Loss
DRG-LLaMA[18]	236,192	Healthcare	Multi-class Classification	F1-score, AUC
APR-DRG[19]	63,681	Surgery	Mortality Prediction	c-statistic, Brier score

Table 1: This table provides a comprehensive overview of various benchmarks used in the evaluation of healthcare payment reforms. It details the size, domain, task format, and metrics for each benchmark, highlighting their relevance in assessing financial and clinical outcomes in healthcare systems.

Assessing the cost-effectiveness of healthcare payment reforms requires a diverse set of metrics that capture both financial and clinical outcomes. Key indicators include hospital efficiency, resource utilization, Length of Stay (LOS), readmission rates, and expenditure per patient case, which collectively measure the operational efficiency of healthcare providers and the effectiveness of payment reforms in managing costs and patient care [4]. Table 1 presents a detailed summary of key benchmarks employed to evaluate the effectiveness of healthcare payment reforms, illustrating the diverse metrics and domains involved in this critical analysis.

A critical metric is the accuracy of Diagnosis-Related Groups (DRG) classification, which directly affects hospital reimbursement and financial management. Accurate DRG assignments are essential for fair resource distribution and cost management; inaccuracies can lead to financial issues such as upcoding or downcoding, impacting revenue. For instance, in a Malaysian teaching hospital, misclassifications led to potential income losses exceeding RM654,000. Changes in DRG classification, such as those implemented by Medicare, show that hospitals may adjust coding practices in response to incentives, affecting revenue and spending efficiency. Thus, maintaining high coding accuracy is crucial for the integrity of DRG-based payment systems [9, 16, 6, 20]. Advanced models like DRG-LLaMA and KG-MTT-BERT enhance DRG classification accuracy, improving this metric's reliability.

The impact of payment reforms on patient outcomes is another essential metric, encompassing patient satisfaction, clinical quality indicators, and health outcomes. These metrics are vital for assessing the broader effects of payment reforms on healthcare quality and patient well-being. For example, Dynamic Incentive Programs (DIP) have been linked to changes in clinical practices and patient care, highlighting the importance of evaluating these reforms' effects on healthcare delivery and outcomes [4].

Technological innovations in payment systems, such as machine learning and natural language processing (NLP), provide new metrics for evaluation. These technologies improve data processing accuracy and efficiency, enhancing performance metric assessments and enabling dynamic payment mechanism adjustments [10]. Integrating these data-driven approaches into payment reform strategies is crucial for optimizing healthcare delivery and ensuring financial sustainability.

The metrics for evaluating the cost-effectiveness of payment reforms are multifaceted, encompassing financial indicators like total hospital costs and reimbursement rates, alongside clinical outcomes such as LOS and patient health status, and technological factors assessing healthcare delivery systems' efficiency [4, 6, 13, 3]. This comprehensive framework allows healthcare systems to refine payment strategies, enhance operational efficiency, and improve patient outcomes.

7.2 Case Study: APR-DRG ROM Model

The All Patient Refined Diagnosis-Related Groups (APR-DRG) Risk of Mortality (ROM) and Severity of Illness (SOI) subclasses offer a refined approach to clinical risk assessment and in-hospital mortality prediction, surpassing traditional models like the Charlson Comorbidity Index in predictive accuracy. Validation studies confirm their enhanced capability in estimating in-hospital mortality likelihood, highlighting their utility in clinical risk management [19].

This case study underscores the importance of advanced classification systems, such as the APR-DRG ROM and SOI subclasses, in healthcare. These systems are vital for precise risk stratification, essential for improving patient outcomes and ensuring effective resource allocation, particularly in perioperative contexts where accurate mortality risk predictions significantly influence clinical decision-making and patient safety [19, 20]. The APR-DRG model's ability to refine patient classification based on detailed clinical data enables tailored interventions, aligning treatment plans with individual patient needs and enhancing overall care quality.

The implications of the APR-DRG ROM model extend beyond mortality prediction. By improving patient categorization precision, this model supports better clinical decision-making and resource management. Hospitals can leverage insights from recent DRG reimbursement structure changes to identify and prioritize high-risk patients effectively, optimize resource allocation, and implement tailored care strategies for diverse patient populations. Analyzing patient data through refined classification systems enables hospitals to manage healthcare costs more effectively and improve patient outcomes while addressing challenges such as upcoding and diagnostic ambiguity from pursuing higher reimbursements [16, 3, 8, 6, 4].

Integrating the APR-DRG ROM model into healthcare systems exemplifies the shift towards data-driven healthcare management. By utilizing advanced data analytics and innovative classification methods, such as the KG-MTT-BERT model, healthcare providers can significantly enhance risk assessment precision and care quality. This approach addresses the complexities of medical text and DRG classification while fostering the development of more effective and sustainable healthcare systems through continuous updates based on real-case data. These advancements contribute to a more transparent, efficient, and responsive healthcare environment that better meets the needs of patients and providers [14, 7, 19, 20, 8].

8 Challenges and Future Directions

8.1 Regulatory and Systemic Challenges

The integration of Diagnosis-Related Groups (DRG) and Dynamic Incentive Programs (DIP) in healthcare systems faces substantial regulatory and systemic obstacles, such as upcoding and diagnostic ambiguity, which undermine the efficacy of these payment reforms and impede efforts to improve healthcare efficiency while managing escalating costs [6, 13, 3, 8, 4]. A significant regulatory issue is the reliance on discharge summaries for DRG predictions, which often lack the comprehensive clinical data required for accurate classification. This limitation is highlighted in studies where data constraints hinder the reliability of DRG assignments.

Additionally, the generalizability of findings from research conducted in specific healthcare settings poses a systemic challenge. Studies confined to a single teaching hospital may not accurately represent the broader applicability of DRG systems across various healthcare environments, thus limiting the potential for widespread implementation and standardization [9]. The complexity of comparing Risk of Mortality (ROM) and Severity of Illness (SOI) subclasses across different DRGs further complicates matters, as administrative data may not match the accuracy of manual chart reviews [19].

The DIP system also confronts challenges like upcoding and diagnostic ambiguity, necessitating continuous reform efforts to clarify and refine healthcare payment mechanisms [4]. These issues are compounded by the limited capacity of existing benchmarks to account for external factors affecting patient coding, including demographic changes and concurrent healthcare reforms, complicating regulatory oversight [15].

Addressing these regulatory and systemic challenges requires the development of robust frameworks capable of accommodating the complexities of healthcare delivery and the myriad factors influencing hospital performance. To ensure DRG and DIP systems effectively enhance healthcare efficiency and quality, it is essential to improve the interpretability and traceability of diagnostic systems. Expanding research to encompass a broader range of healthcare environments is also critical, particularly in light of managerial workarounds in DRG implementation, as demonstrated by case studies from England, Germany, and Italy. Employing advanced natural language processing frameworks to tackle issues like write-missing diagnoses can further enhance the integrity of these systems, leading to more accurate and comprehensive patient care outcomes [15, 8].

8.2 Future Research Directions

Future research in healthcare payment reform should prioritize several key areas to enhance the efficacy of models such as the dual-layer principal-agent framework and associated payment mechanisms. A crucial research focus is the long-term impact of upcoding practices on patient outcomes and the regulatory effectiveness of measures aimed at mitigating these practices. Understanding these dynamics is essential for developing more robust payment systems that balance financial incentives with the quality of patient care [16].

Research should also explore the integration of additional clinical data sources, such as admission notes, to improve DRG prediction accuracy and address limitations identified in existing studies [18]. Furthermore, broader studies across multiple hospitals are necessary to validate findings and examine the influence of physician documentation on coding accuracy [9]. These efforts could lead to more reliable DRG systems, thereby enhancing healthcare delivery and financial management.

The development of refined payment standards and the incorporation of ethical considerations into healthcare payment reform represent another critical research direction. Longitudinal studies assessing the quality of care under DRG systems can yield insights into the long-term impacts of these payment models, informing the creation of more equitable and effective healthcare policies [3].

Additionally, future research should encompass broader investigations of the DIP system's impacts across various specialties and include long-term follow-ups to validate findings [4]. This exploration should consider the effects of financial incentives on healthcare quality and assess the feasibility of adapting DRG systems across diverse healthcare contexts [5].

Evaluating the benefits and drawbacks of ICU utilization at the end of life and enhancing palliative care services is another essential area for future research, aiming to improve patient outcomes and optimize resource allocation [23]. By addressing these research domains, future studies can contribute to the development of more effective and sustainable healthcare payment systems that enhance both cost-effectiveness and quality of care.

9 Conclusion

The exploration of the dual-layer principal-agent model within healthcare payment reforms, particularly through Diagnosis-Related Groups (DRG) and Dynamic Incentive Programs (DIP), underscores their transformative potential in enhancing healthcare efficiency and cost management. The shift to DRG systems signifies a critical evolution from fee-for-service models to prospective payment frameworks, promoting standardized payments based on clinical attributes and resource consumption. This transition has facilitated improvements in hospital operations and expenditure control, notably in regions like China and South Korea.

However, the implementation of DRG systems is not without challenges, such as upcoding and classification inaccuracies, necessitating continuous refinement and regulatory vigilance to ensure equitable resource distribution and prevent misuse. Technological advancements, including machine learning models, provide promising avenues for improving classification precision, thereby enhancing performance assessments and resource allocation.

Dynamic Incentive Programs (DIP) complement these systems by aligning financial incentives with provider performance, encouraging the integration of innovative practices and technologies that enhance care delivery and resource use. The application of self-supervised learning models exemplifies the technological progress facilitated by DIP, contributing to improved diagnostic accuracy and patient outcomes.

The dual-layer principal-agent model offers a comprehensive framework for analyzing the complex interactions among healthcare stakeholders, emphasizing the necessity of aligned incentives and innovative payment strategies for sustainable healthcare systems. Future research should aim to refine these models, explore their long-term impacts, and tackle regulatory and systemic challenges to bolster the effectiveness of payment reforms, ultimately enhancing healthcare quality and financial sustainability. By leveraging advanced technologies and data-driven approaches, healthcare systems can continue to evolve, ensuring the delivery of high-quality, cost-effective care that meets the diverse needs of patient populations.

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