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ABOUT THE COVER

Denton Reflection #1

Gretchen Busl is a Professor in the English, Rhetoric and Spanish Department and the Quality Enhancement Plan Director at Texas Woman's University. She earned a PhD in Literature from the University of Notre Dame and a BA in Romance Languages from Mount Holyoke College. She is currently pursuing a BFA at TWU.

We would like to thank the TWU Libraries' Design Specialist, Sean Spear, for designing our journal cover.

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A Message from the Editors

The TWU Student Journal continues its work! This journal exists to offer opportunities for students to share original scholarly and creative works, and to gain experience with peer review, open publishing, and other journal production ideas and processes.

The Spring 2024 edition (Issue 3), contains three articles. We offer space here for an exploration of the way Artificial Intelligence bears on healthcare, the working conditions of nurses in need of mandatory breaks (and meals), and the experiences of African international students. There is an element of advocacy in these works, which perhaps reflects important aspects of TWU's identity – heart, grit, and compassion.

This ongoing work is only possible with the support of our many allies. Thanks especially to the TWU Libraries, the School of Library & Information Studies, our Advisory Board, to Student Editor Madeline Ray, and to Dr. Gretchen Busl and Sean Spear for the cover art and design.

We hope you will enjoy learning from our student authors' scholarship and experiences, and share this issue widely.

TWUSJ Editorial Team

School of Library & Information Studies Faculty:

Ahmet (Meti) Tmava, PhD, wrote his dissertation on faculty perceptions of open access repositories. Dr. Tmava designed and is teaching a graduate course on scholarly communication, and serves as a peer reviewer for several academic journals.

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Adrian Shapiro, MLS, Manager of Digital Initiatives and Assessment, serves the TWU community with her involvement in the Texas Digital Library and the management of the university's institutional repository, the Repository@TWU.

Elizabeth Headrick, MLS, Digital Scholarship Librarian and TWU PhD Candidate in Rhetoric, is focused on Open Access and Open Educational Resources.

Kenneth (Woody) Evans, PhD, MLIS, is the Research and User Experience Manager at the Blagg- Huey Library.

Student Editor:

Maddie Ray, Maddie Ray is currently an undergraduate student majoring in Political Science and is a former managing editor for The Lasso. She is passionate about equitable and inclusive university practices.

In this issue, our authors present work from various disciplines including nursing, psychology, and health care.

Thank you to our wonderful student writers for their contributions!

TWUSJ Advisory Board

African International Student Representation in the Literature: A Scoping Review

Ijeoma Azike-Muolete

Abstract: International student enrollment has steadily increased since the 1960s, and international students can be found in colleges and universities across the United States. African international students are a subset of this population, and this scoping review examines the extant literature to explore what is known about the experiences of African students in U.S. universities and the implications of those findings. We identified three themes including racism and racial identity, social capital/network, and resiliency factors of this population.

Keywords: African international student, scoping review, mental health, resiliency factors.

Introduction

During the 2020/21 academic year, 914,095 international students were enrolled in U. S. universities, and African international students made up 10% of overall international students in the United States (Institute of International Education, 2021). The economic impact of international students in the United States is well documented (Hegarty, 2014) and indicates that American universities rely on this population for continuous growth. International students have been a part of United States higher education since the 1940s (Institute of International Education, 2021) and contributed over $28 billion and 300,000 jobs to the U.S. economy in 2021 alone (NAFSA, 2021). Hegarty (2014) explored the growing influence of international students and their importance in higher education enrollment. Existing research has explored the different stressors that international students experience but the literature on the well-being of African international students in the United States is emergent and sparse (Alharbi & Smith, 2018).

African youth and young adults moving to the United States to enroll in higher education programs are vulnerable to a wide range of stressors accompanying the transition (Hansen et al., 2018; Campbell, 2015). Protective factors, such as the presence of family in the United States vary for international students. While international students may already have family members, friends, or old acquaintances in the United States, others arrive with a social network intact. Research shows that international student stressors lead to adverse effects like depression, anxiety (general and academic), and mental health challenges (Kim et al., 2019) that affect development and reduce the quality of life for the individuals as well as their family.

The research on the wellbeing and mental health of African immigrants in the United States is both emergent and well documented (Alharbi & Smith, 2018; Abimbola, 2021; Ahmed & Rasmussen, 2020; Escamilla & Saasa, 2020). The isolation that accompanies the move is one that may not always be captured in the research. For international students, these stressors may be heightened by additional factors such as culture shock and acculturation stress as they struggle to adjust to new cultural norms and preserve their connection to their home culture and families. Research suggests that acculturation stress is prevalent among the general international student body. The diverse ways by which they cope depend on different variables such as home culture, age, individual experiences, and the motivation to complete their education in the United States (Hansen et al., 2018; Campbell, 2015). Quality of life increases for African international students and their families when policies and educational practices help students to better cope with stressors. Minutillo et al. (2020) suggested that services provided to international students should be specific to individuals. Providers of these services should be aware of the differences in culture and perceptions of international students from different regions, countries, cultures, and languages. Research influences policies and educational decisions which, in turn affect students, both domestic and international (Campbell, 2015). Scholarship on international student experiences in the U.S. should be representative of the diverse population that make up the international

student body. Due to the gap in the literature on stressors and protective factors unique to African international students, we conducted a small-scale scoping review to map the findings of recent literature on African international students in U.S. institutions. Specifically, we ask the following question: what is known about the well-being and experiences of African international students in U.S. universities?

Method

We used scoping review methodology (Arksey & O'Malley, 2005) to explore patterns and themes in the extant literature on the well-being and psychosocial adjustment of African international students attending U.S. universities. One of the advantages of scoping reviews in comparison to other synthesis methods (e.g., systematic literature reviews, meta-analyses) is that this method is well-suited for exploring the breadth of what is known about a topic that is under examined. That is, scoping methodology is useful for "mapping" multiple dimensions of existing research, such as similarities and differences in methods, theoretical frameworks, findings, and empirical gaps (Jensen & Sanner, 2021; Peters et al., 2015). In the present paper, we followed Arksey and O'Mally's (2005) five-step process for conducting scoping reviews, including (1) identifying the inquiry question, (2) identifying relevant studies, (3) study selection, (4) charting the data, and (5) reporting results.

Articles Selection

The databases searched during this scoping review include (APA PsychINFO, APA PsychArticles, and SocINDEX, Education Source). The initial search was conducted in March 2022 followed by another search in April 2022. The inclusion criteria used to identify relevant articles included empirical articles published in peer-reviewed journals between 2012-2022 whose sample consisted of African international students attending U.S. institutions. The following keywords were used to narrow the search: "African international students" AND "foreign-born students in the U.S." AND "international students of color." This yielded a total of 88 articles. After reviewing the titles, abstracts, and main text, 80 articles were excluded due to not meeting criteria. Inclusion criteria was expanded to include a mixed sample population that included African international students and international students from other countries due to the limited amount of research found on this population.

A total of 10 articles were included for the scoping analysis and are listed in Table 1.

Table 1:

Authors	Year	Title	Methods
Ashong, C., & Commander, N.	2017	Brazilian and Nigerian international students' conceptions of learning in higher education.	Qualitative research-use of interviews and reflective diaries.
Briscoe, K. L., Yao, C. W., Oates, E. Q., Rutt, J. N., & Buell, K. J.	2011	Perceptions of social networks among first-year international students of color.	Qualitative research – use of interview (longitudinal study of one year)
Fries-Britt, S., George Mwangi, C. A., & Peralta, A. M.	2014	Learning race in a U.S. context: An emergent framework on the perceptions of race among foreign-born students of color.	Qualitative research – focus groups
George Mwangi, C. A., Changamire, N., & Mosselson, J.	2019	An intersectional understanding of African international graduate students' experiences in U.S. higher education.	Qualitative research - counter stories
Manyibe, B. M., Manyibe, E. O., & Otiso, K. M.	2013	College student leadership development: An examination of pre-college leadership development of African students in the United States.	Qualitative research – phenomenological design
Koo, K. K., Yao, C. W., & Jung, G. H.	2021	"It is not my fault": Exploring experiences and perceptions of racism among international students of color during COVID-19.	Qualitative method – focus groups

Mangwo, A., Whitney, S., & Chareka, O.	2013	The role of volunteerism on social integration and adaptation of African students at a Mid-Western university in the United States.	Qualitative research - interviews
Omotosho, S.	2018	Live experiences of African nursing students: Insights for enhancing international students' success.	Qualitative research - phenomenology
Shadowen, N. L., Williamson, A. A., Guerra, N. G., Ammigan, R., & Drexler, M. L.	2019	Prevalence and correlates of depressive symptoms among international students: Implications for university support offices.	Quantitative research – hierarchical multiple regression model
Sparks, D. M., Nandakumar, V., & Njock Libii, J.	2019	"We are shaped by our experiences" intersectionality and the African international STEM student.	Qualitative research interview and case study

Articles Synthesis

To analyze and synthesize the findings across the 10 selected articles, a literature review table was created to extract key design elements, sample size, sample characteristics, research question(s) or purpose, methods, results, and implications. The literature review table allowed for a compilation of chosen articles, making for easy access to information. Next, a synthesis table was used to facilitate the grouping and comparison of major findings. The lead author used a color-coding strategy to map similarities within and across content. The synthesis table allowed for easy access to study results and made comparisons across study results accessible, leading to the identification of major patterns. Analysis of major patterns were focused on answering research questions about African international students, paying attention to emerging trends and gaps in the literature. The second author reviewed the emerging themes identified by the first author, and inconsistencies were discussed by both authors leading to clarification about the relationship between themes and the extracted literature content.

Results

This small-scale scoping review was undertaken to answer the following research question: what is known about the well-being and experiences of African international students in U.S. universities? While the 10 studies all reported on African international students in the U.S., they differed in their methods and findings. This scoping review found three major themes pertaining to the research that include racism/racial identity, social capital/network, and resiliency factors of African international students. First, we report on the participant characteristics of the samples used in the studies. Next, we present findings that correspond

to the research question regarding the prevailing themes in the research on this population. Finally, we answer the research question by describing the three major themes identified in
the synthesis.

Participant Characteristics

Participants across the 10 articles included adult men and women between the ages of 18 and 45 years, born across countries in East, Southern, and West Africa, living away from family, and enrolled in both undergraduate and graduate programs in the U.S. Participants' time living in the U.S. ranged from 1 to 12 years. Participants were Africans from different countries in the continent with varying perspectives, cultural values, and experiences.

Findings for Research Questions

The scoping review revealed that there is limited scholarship of African international students' experiences in peer-reviewed research. Five of the 10 articles reviewed specifically explored African students, while the other five articles used combined samples of international students from various continents (Asia and South America). We found that African international students are underrepresented in the literature on international students, leading to an under examination of their experiences. However, the overarching subject-matter included the experiences of African students known as acculturative stress, and our scoping review found three themes including racism and racial identity, social capital/network, and resiliency factors.

Theme 1: Racism and racial identity

Fries-Britt et al. (2014) found in their study that African international students have little to no conceptual understanding of racism and racial discrimination in the U.S. due to their own national background and socialization, racial issues are initially perceived as foreign, and unlike their African American counterparts. Yet, Koo et al. (2021) and Fries-Britt et al. (2014) found that participants' experiences of subtle or overt racism eventually led to an analysis and conceptualization of racism that relates to their own identities. Spark et al. (2019) concluded that the home cultures of participants influence and possibly guide their attitudes as they matriculate through their programs. International students from Africa have a different concept about race; Sparks et al. (2019) also found that their understanding of race was based in concepts such as tribalism and reflected substantive differences compared to their U.S. born African American peers. Omotosho's (2022) survey of nursing students regarding their experiences in the U.S. that students focused on their education and opportunities resented the way that American media presented race and race relations.

Sparks et al. (2019) noted that while African American students may consider race a part of their identity due to their environment, African students have to learn about race and go through a process of analyzing and understanding their position in a highly racialized society like the U.S. Shodowen et al. (2019) analysis of data concluded that a 45% of African students reached or exceeded the threshold for the symptoms of clinical depression and 24% for anxiety as a direct result of their experiences far away from home and support. Research shows that African American students have been historically exposed to racism and racial discrimination (Pettigrew, 1988; as cited by Sparks et al., 2019) and African students go through the process of experiencing, analyzing, and lastly reaching a climax where they form their own racial identity just like their African American counterparts. The process of reaching that racial identity for African students is different from native-born students (Ashong and Commander, 2017) and may lead to feelings of loneliness and isolation (Koo et al., 2021) and trigger mental health issues like depression and anxiety (Shodowen et al., 2019).

Theme 2: Social capital/network

Research on international students documents their experiences, both positive and negative, while recommending interventions to help (Minutillo et al., 2020; Hansen et al., 2018; Campbell, 2015). African student-built relationships and networks helped them feel a sense of belonging and facilitated opportunities perceived as supporting their future professions and lives. Mangwo et al.'s (2013) found that for African students - volunteering, learning new skills, and building upon existing skills helped encourage relationships with host communities, which could possibly mitigate negative experiences of acculturative stress. In the same vein, Mangwo et al. (2013) also recognized the disadvantages that volunteering caused to participants increasing negative experiences. While the importance of building social capital or network cannot be over emphasized, Briscoe et al. (2022) highlighted the difficulties that came with building those relationships with domestic-born students. Briscoe et al. concluded that the negative perceptions that African students have of their American classmates prior to arriving in the country may be a hindrance to building long-term relationships as well as experiencing racism (Koo et al., 2021; Fries-Britt et al., 2014).

Briscoe et al. (2022) also found that due to the difficulty in making friends with native-born students, African international students built homophilic relationships with students from their own countries and with international students from other countries before attempting to make friends with their American counterparts. George Mwangi et al. (2019) postulated in their study that wrong and negative assumptions prior to moving to the U.S., lack of support facilities, and pressure to assimilate and quickly adhere to U.S. standards may contribute to negative experiences of transition, hence participants sought relationships with students that could relate to their experiences.

Manyibe et al. (2013) and Mangwo et al. (2013) found in both studies that participants honed their skills through building social networks and capital prior to their move for school and during the course of their education in the U.S. even though learning styles and concepts (Ashong & Commander, 2017) were different from what they were used to. Researchers found that African international students' experiences, even while it had negative impacts, kept them focused on their goal. Their focus on their objectives may become an anchor to see their goals through.

Theme 3: Resiliency factors

Previous themes in the present study showed that African students have a myriad of experiences as they matriculated through their programs. Shodowen et al. (2019) demonstrated the presence of clinical depression and anxiety symptoms with this population; Omotosho (2018) demonstrated the negative effects of isolation and detachment from participants' home countries; and George Mwangi et al. (2019) demonstrated how host universities use the diversity rhetoric to admit African international students without giving them the support they need to thrive in their environment. Even though there are opportunities to pursue dreams and goals (Omotosho, 2018), the lack of support (George Mwangi et al., 2019) and resources to adjust, the levels of anxiety symptoms (Shodowen at al., 2019) did not discourage the participants to pursue their goals (degree) and focus on their academics. Sparks et al. (2019) concluded that the influence from home cultures and the leadership skills learned within the families and communities (Manyibe et al., 2013) allowed participants to build relationships and find their own support systems, mitigating acculturative stress, as they transitioned into their host communities.

In a racialized society like the United States, students from Africa expect to be racially discriminated against (Koo et al., 2021) even when they do not understand the history and concept of racism (Sparks at al., 2019). But they focus on their studies, academic achievements, support systems, and build social capital in their host communities. Shodowen et al. (2019) showed in their study, that even with only 2% African students' representation in the sample size, social support positively influenced depressive symptoms. This means that African students build social support, homophilic relationships, and friendships that encourage completion of objectives irrespective of problems. This is not to say that there are no psychological effects as Shodowen et al. (2019) reported the prevalence of depressive and anxiety symptoms. Even though negative perceptions of domestic students were reported to be present in participants, they attempted to build friendships and relationships with domestic students within their first year (Briscoe et al., 2022).

Implication and limitations

The present scoping review sought to examine and understand how African international students are represented in the research, both the extent and patterns in the findings. The review searched for and identified peer reviewed articles using specific criteria for eligibility and further synthesized the studies to understand how African international student issues are documented. The present review found that African international students are represented in the literature if only on a minuscule scale. The review also found emerging themes that postulate how African students are represented in the literature, which included how racism and racial discrimination affect the identity of these students. The importance of building and sustaining social support and systems, and the resiliency factors of this population that revolved around social support systems. This review has limitations, which includes the size of the reviewed articles. For a nuanced understanding of how African international students are represented in research, a larger number of articles should be reviewed as they will cover more aspects and have larger sample sizes. This will be a benefit when making laws, policies, and educational decisions that will affect this population and could possibly affect domestic students as well.

This scoping review has several implications for research, practice, and policies. For research, there is a need to further explore this population in order to understand the specific issues of acculturative stress as well as culturally sensitive ways to mitigate those issues. Future research should consider this population's resiliency factors and how they can help mitigate issues like racism, isolation, loneliness, and mental health. These findings will help in educational decisions and policies affecting this population.

Conclusion

Our scoping review revealed that empirical research on African international students in the United States scant. Scholarship produced within the last ten years offers insight on multiple dimensions of African international students' experiences including the influence of experiences prior to moving to the United States, transition periods, and post-graduation plans. International students from Africa are a growing population in colleges and universities across the nation. Therefore, it is important that their experiences are documented, and that culturally sensitive interventions are implanted on their behalf. Colleges and universities should also pay attention to this section of their student population; not just admissions acceptance rates, but in provision of services that will benefit them academically, professionally, and personally.

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Navigating the Risks of Artificial Intelligence Foundation Models in Healthcare: How Health Systems Can Respond

Warren Poquiz [1]

Abstract: Foundation Models (FMs) have unveiled a new phase in the Artificial Intelligence (AI) era, characterized by significantly larger datasets and massive computational power. This analysis examines the applicability of FMs in the healthcare sector and how their advanced functionalities, such as in-context learning, can enhance overall organizational performance by increasing efficiency, accuracy, and predictability. However, scholarly works over the past decade have primarily focused on the implications of AI's pervasive application in society, and there remains a critical need to deepen the discussion on AI governance, particularly in the healthcare domain. The rapid advancement of AI models, combined with insufficient regulatory oversight, poses significant risks to patients and Healthcare Organizations (HCOs), including privacy breaches, adversarial attacks, model opacity, and algorithmic biases. To address these risks, this paper calls for the promotion of a three-layer governance structure for HCOs based on the hourglass model for AI governance by Mäntymäki et al. (2022).

Introduction

The rise of Generative Artificial Intelligence (AI) is quickly shaping the Fourth Industrial Revolution. AI's computational prowess and advanced algorithmic capabilities have ushered in an era never seen in history while presenting new challenges in navigating the intricate play between machine intelligence and human existence. Recently, there has been a surge in popularity with the use of Large Language Models (LLMs) such as the Generative Pre-Trained Transformer (GPT). LLM is a significant advancement in Natural Language Processing (NLP), a subset of AI explicitly focusing on a computer's ability to comprehend text and spoken words like humans. NLP has revolutionized digital technology through its contributions, such as chatbots, virtual assistants, and language translation. However, the emergence of LLMs and their ability to train on large amounts of data significantly enhances current NLP features by providing contextually relevant texts based on memory. In healthcare, the profound benefits of these models offer an innovative solution to longstanding problems in care delivery.

Notably, the rapid rate at which technological innovations have permeated society characterizes the reduction in the lag of momentous technological advancements in the

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twentieth century. For instance, it took more than 200 years from when the steam engine was developed to when Henry Ford built the first car, while it only took less than 50 years from the first call on a wireless handheld device to the development of smartphones with embedded AI technology (Makridakis, 2017). The same pattern can be observed in ChatGPT's latest LLM GPT-4 release, less than a year after its previous groundbreaking iteration (GPT-3) went public in 2022. Subsequently, many renowned names who hold pragmatic views of the technology, including Tesla CEO Elon Musk, warn about AI's "profound risk to society and humanity" and call for a halt on AI training for at least six months (Future of Life Institute, 2023). Geoffrey Hinton, widely known for his works in deep learning and neural networks, also warns about the dangers of AI and calls for urgent investment in AI safety and control (Kleinman & Vallance, 2023). This significant challenge in technological shifts mirrors the inability of governance initiatives to keep up with rapid innovative advancements. For this reason, the World Economic Forum published a white paper articulating that reliance on government legislation regarding rapidly advancing technology is ill-advised as it is likely to be outdated before implementation (2016).

Over the past decade, numerous studies have predicted and outlined the effects of widespread AI use in society; however, the specific focus on AI governance needs to be expanded in the literature, especially in healthcare. This essay will answer two fundamental research questions: What are the inherent risks of an AI-driven healthcare organization (HCO), and how can HCOs appropriately respond to these risks? The paper will identify four potential implementation risks associated with Foundation Models (FMs) in the healthcare landscape and call to promote a three-layer governance structure guided by the principles of ethical AI and applicable regulations.

Foundation Models: The Key To AI-Driven HCOs

"Foundation Models" or FMs is a term coined in 2021 by the Stanford Institute for Human-Centered Artificial Intelligence (HAI) (Bommasani et al.,2021). Bommasani et al. define the term as "any model that can be trained on broad data," adapted, or fine-tuned to a wide range of downstream tasks. The Center for Research on Foundation Models (CRFM) simplifies the definition: train a single model on a vast dataset and customize it for various applications (n.d.). Notable examples of FMs in deployment include LLMs like GPT-3. While LLMs are tasked explicitly with generating and interpreting human-like texts, FMs generally have a broader application by integrating multiple modalities (text, images, videos, etc.) across different models with specific tasks or purposes. This training process is illustrated below:

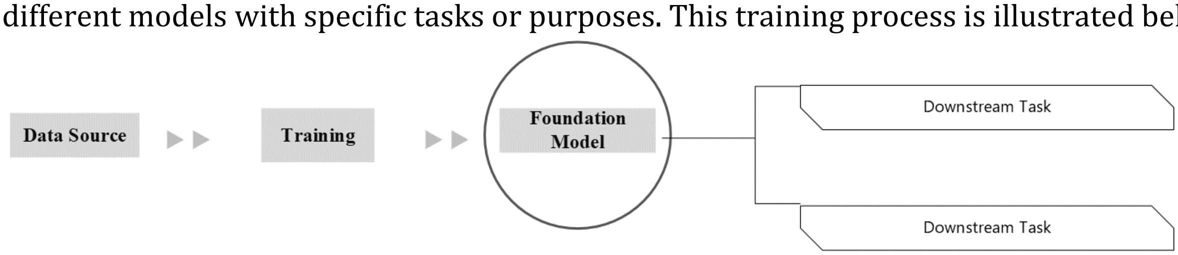

Fig.1 Foundation Model Framework

FMs are rooted in the principles of Artificial Neural Networks (ANNs) and Self-Supervised Learning (SSL), both concepts that have existed for decades (Bommasani et al., 2021). ANNs are systems consisting of artificial neurons, organized in layers, that mirror the behaviors and functions of the human brain. On the other hand, SSL is a type of learning wherein the data "supervises itself for training the model" and instructs its network on what is right or wrong (Rani et al., 2023, p. 2761). The principle behind SSL was derived from how infants learn through observation with little interaction with their surroundings (Rani et al., 2023). Further, since SSL works on unlabeled data, it virtually eliminates the time-consuming and often costly manual annotation of data. However, what makes FMs so fundamentally powerful compared to other AI models is their ability to simultaneously apply the principles of ANNs and SSL at a much larger scale, often measured in parameters. A model's parameter correlates with its ability to discern complex patterns from the data; thus, the greater the parameters, the more it yields superior outputs. For example, GPT-3 has a scale of 175 billion parameters or nearly 45 terabytes of text data (Broadhead, 2023). While training data for GPT-3 is currently not publicized, it is estimated that the model was trained on 500 billion words from the internet (The Alan Turing Institute, 2023). GPT-3's previous iteration (GPT-2), released in 2019, only had 1.5 billion parameters.

The swift progress in scale can be linked to the exponential growth of computational power, also known as "compute," accessible for training datasets. The compute consumption in LLMs like GPT-3 is measured in petaFLOPS-days—the number of computations performed in one day by a computer calculating a thousand trillion computations per second (Power, 2022). GPT-3 required 3,640 petaFLOPS-days to train. A standard laptop would take several thousand years to reach the same number of computations used in training GPT-3. A 2012 paper highlighting an image classification architecture popularly known as "AlexNet" demonstrated how increased computing power can lead to superior results (Krizhevsky et al.,2012). The model in the study outperformed human-level accuracy in image recognition by simply increasing computing power in training a convolutional neural network. These findings led researchers to believe that increasing compute in training top models would lead to better performances, subsequently resulting in a significant rise in computing demands (Power, 2022). From 1959 to 2012, computing power generally doubled every two years; however, since the 2012 study, computing power has doubled every three and a half months (OpenAI, 2018).

In healthcare, applications of AI models have historically been isolated to high-level predictive capabilities of Deep Learning (DL) algorithms for single-purpose tasks such as enhancing image analysis to recognize potentially cancerous lesions in radiology (Fakoor et al., 2013) or risk scoring models such as predicting congestive heart failure (CHF) and chronic obstructive pulmonary disease (COPD) based on clinical data (Cheng et al., 2016). With the advent of FMs, the applications of AI in healthcare now also include advanced functionalities such as in-context learning—the ability to learn from a few examples in the context through analogy (Dong et al., 2022). Fig. 2 visualizes the application of an FM in a healthcare organization. The data is extracted from multidisciplinary sources in care delivery that include both clinical and non-clinical stakeholders. The data gathered will generate multimodal inputs such as clinical notes, diagnostic history, or key performance indicators (KPIs), including financial and operational margins. The foundation model will be trained on this data to be applied to several downstream tasks in the health system, such as personalized medicine and context-based chatbots for the patient, efficient assistive tools in diagnosis and treatment for the providers, and analytics dashboards that will aid administrators in making informed decisions based on accurate real-time data across various organizational functions. Previous research has also proposed a comprehensive application of DL techniques in healthcare organizations similar to the functionalities of an FM (Miotto et al., 2018). However, the study suggested models that must be constantly updated to follow the changes in patient populations, which can be labor-intensive and expensive. FMs do not focus on specific tasks as they capture a wide range of knowledge from broad organizational data, thereby eliminating the need to train other models in the system from scratch.

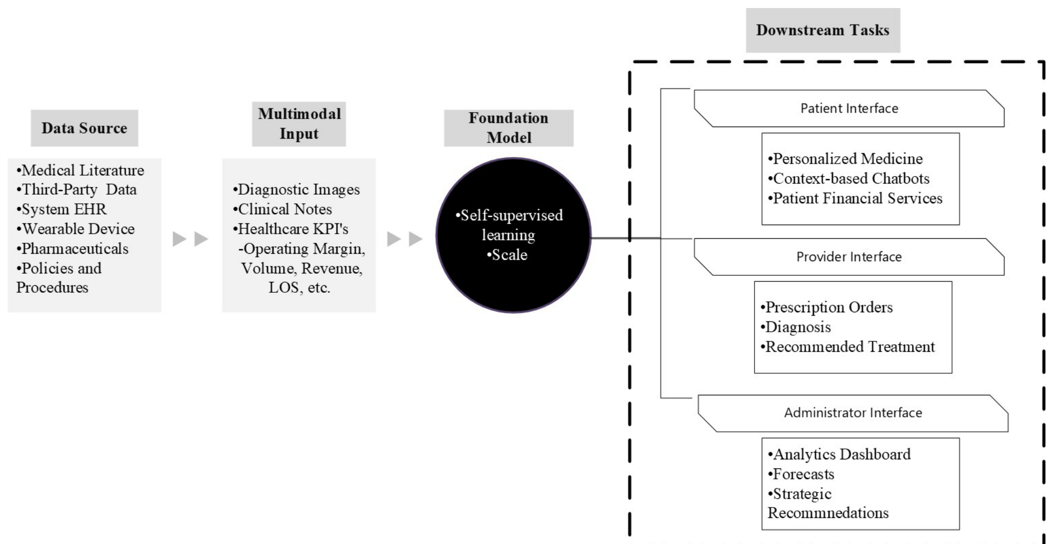

Fig.2 Foundation Model Application in Healthcare (Adapted from Bommasani et al.,2021)

Risks

As FM discussions continue to integrate into healthcare, it becomes imperative to understand the inherent risks posed by implementing them in the healthcare workflow, including privacy, security, explainability, and fairness.

The HIPAA Privacy Rule in the Age of AI

Given the magnitude of the datasets required to train AI systems, it is no surprise that the safeguarding and privacy of data have constituted focal points in most AI legal challenges. AI's hunger for massive amounts of information and healthcare's highly regulated landscape will make it challenging to coordinate the exchange of health information between HCOs and AI developers. In a 2019 class action lawsuit, a patient sued Google and the University of Chicago Medical Center for alleged disclosure of medical information of nearly every patient from the hospital system without removing detailed time stamps and clinical notes. Google assured that data were de-identified, which the plaintiff claimed to be highly misleading, citing Google's tremendous data mining capabilities make them "uniquely able to determine the identity of almost every medical record the University released" (Dinnerstein v. Google, 2019). *Dinnerstein v. Google* raised questions about whether complete anonymization of data can be actually achieved, especially with the cross-linking capabilities of modern technology. Previous research has demonstrated compromised anonymity in genomic studies where anonymous participants can be identified by analyzing Y-chromosome sequences from public genealogy websites containing their distant relatives' surnames (Gymrek et al., 2013). Another study evaluated an algorithm's ability to re-identify thousands of physical activity data in wearable devices that have de-identified health information and found that the algorithm successfully re-identified more than 80% of the demographic (Na et al., 2018). The *Dinnerstein* case suggests that current anonymization practices do not prevent large digital companies from cross-linking geographical coordinates of Google users and their exact dates and times of arrival and departure from specific locations to timestamps in the health record, identifying anonymous patients by name, physical and email addresses, duration of encounter, etc. (Dinnerstein v. Google, 2019).

The Health Insurance Portability and Accountability Act (HIPAA) authorizes the disclosure of de-identified medical records by third parties as long as there is a low risk that information could be used "by an anticipated recipient to identify an individual who is a subject of the information" (Standards for Privacy of Individually Identifiable Health Information, 2000). However, technological progress at the time of the rule's passing significantly pales in comparison to the vast scale of technology adoption we are witnessing today. Cohen and Mello discussed the implications of the outdated privacy law and its ineffectiveness in addressing data challenges, calling for a reassessment of data-sharing governance in the 21st century (2019). Data experts have also proposed techniques to virtually eliminate privacy risks, such as using synthetic data with simulated datasets (Gaffney, 2023), while others have taken a much broader approach, shifting the discussion toward data ownership by analyzing patient health information within the intellectual property framework (Liddell et al., 2021).

Security Risks: Adversarial Reprogramming, Overlearning, and Centralization

The vulnerabilities associated with FMs extend far beyond data-related concerns. Security threats can emerge from adversarial access to the model itself. As advanced technology progresses, it also brings about a continued evolution of cybersecurity attacks, frequently targeting high-value subjects such as the healthcare industry through ransomware (Kiser & Maniam, 2021). However, the broad spectrum of AI capabilities introduces new pathways for cyber threats to infiltrate systems that can directly affect the clinical workflow. Thus, the deployment of FMs in HCOs and the healthcare industry must be thoroughly assessed by administrators and regulatory leaders, with a specific emphasis on the unique clinical harm they pose to patients. Due to its infancy, the limited literature on FMs has yet to uncover its full potential, rendering any current deployment more akin to prototypes rather than fully-developed implementations.

One common security flaw in AI models is adversarial reprogramming, where a model is repurposed to perform a new task chosen by an attacker, even if the model was not trained for the task (Elsayed et al., 2018). These attacks are incredibly parasitic in nature as they influence a model's functionality rather than its hardcoded output. For instance, Chu et al. outlined the potential dangers of external adversarial networks that can artificially modify imaging results (output) in radiology (2020). In adversarial reprogramming, which is naturally internal, an attacker would not have to modify an output since the model itself has been repurposed to produce flawed imaging results (such as modifying the lesion size, location, etc.) without the knowledge of its developers or users. This has tremendous implications for clinical decision-making as attacks could potentially result in misdiagnoses of abnormalities and life-threatening conditions.

Another security threat to FMs is overlearning. Song and Shmatikov define the term as a phenomenon where "representations learned by deep models when training for seemingly simple objectives reveal privacy- and bias-sensitive attributes that are not part of the specified objective" (2020). In a healthcare implementation, overlearning specifically concerns the amount of sensitive information that can be accessed or disclosed by covered entities under HIPAA. While the Privacy Rule allows the disclosure and use of health information, it also effectively excludes records that are subject to the Family Educational Rights and Privacy Act (FERPA), including "employment records that a covered entity maintains in its capacity as an employer and [an educational institution]" (Standards for Privacy of Individually Identifiable Health Information, 2000). The overlearning tendency of FMs can potentially de-censor these excluded records by enabling the recognition of sensitive information even if it is not present in the training data. Song and Shmatikov highlighted the inadequacy of privacy protection technologies and the regulations that govern them since there are currently no known techniques to censor these "overlearned attributes" (2020).

This analysis has previously discussed the ability of FMs to homogenize the methodologies adapted to downstream applications. Consequently, this inherent centralization can also represent a single point of failure for all downstream tasks (Bommasani et al., 2021). In essence, previously discussed privacy and security risks where adversaries influence either the model or the data can impact not only one single-purpose task but all downstream tasks in the model. Carlini et al. found that LLMs that have been trained on private datasets can be infiltrated by adversaries to extract private information (2021). This means that FMs that are trained on organizational data run the risk of exposing their private data on all downstream applications for adversarial attacks, including model stealing. A more recent and prominent example of such an incident is the model leak of Facebook's "LLaMa" (Large Language Model Meta AI) in early 2023 (Cox).

Interpretable AI and Clinician Trust

The intricate internal workings of AI models have frequently led them to be widely considered as black box models. A black box model can be either a function that is too complex for human intelligence to comprehend or a function that is proprietary (Rudin, 2019). The ability of FMs to train on a vast amount of complex data enables them to potentially "do unforeseen tasks and do these tasks in unforeseen ways" (Bommasani et al., 2021, p. 123), making them extremely opaque. Further, the predominant focus of interpretability methodologies and initiatives for AI on single-purpose models presents a notable challenge in achieving explainability on FMs because FMs are models influencing an array of other downstream models. In healthcare, the ability to explain and interpret FMs will be critical for user acceptance, trust, and practice of evidence-based medicine. For instance, one study found that the ability to explain and interpret the decision-making process of AI-driven models significantly impacts a physician's behavior towards AI, particularly their trust in the model and intent to use the technology (Liu et al., 2022). Another study highlights the impact of unexplainable models on patient-centeredness, implicating that opaque algorithms can effectively demote patients to "passive spectators in the medical decision-making process" (Amann et al., 2020, p. 8).

While no significant laws currently govern AI in the United States, the General Data Protection Regulation (GDPR) passed by the European Union (EU) in 2018 includes a right-to-explanation provision making it obligatory to explain an algorithm's decision-making process (European Union, 2016). Most major US-based tech corporations must comply with this law as long as they have EU-based consumers, hence the recent emergence of cookie pop-ups on websites asking for consent to collect information. Similarly, the White House Office of Science and Technology Policy (OSTP) released an "AI Bill Of Rights" in 2022 outlining five principles associated with the proper deployment of AI, including explaining an AI system's functionalities in plain language. In 2023, the most comprehensive AI law was effectively passed in the EU—the AI Act. The law aims to address the risks associated with AI without constraining technological development.

One provision of the AI Act allows developers access to "high-quality datasets within their respective fields" (European Union, 2022, p. 29). Enacting a similar law in the U.S. would pose difficulties due to existing privacy regulations within HIPAA. Consequently, Bak et al. predict the possibility of an overall AI ban in healthcare if developers cannot access private health information to test and explain models (2022). These significant regulatory movements indicate that the interpretability and explainability of AI systems will be an integral part of the ongoing discussion toward a comprehensive AI governance structure west of the Atlantic.

AI and Equitable Care

Fairness and bias in algorithms are central concerns in the development and implementation of AI models. Since most models are trained on real-world data, they often reflect inherent societal inequities. Numerous research studies have identified widespread biases in many algorithms deployed in different sectors and functions, including the criminal justice system (Van Dijck, 2022), child protective services (Keddell, 2019), and human resources (Tuffaha, 2023). In healthcare, a 2019 study focusing on racial bias in an algorithm found that black patients were identified to be at a much lower risk than white patients despite being in the same sickness level (Obermeyer et al., 2019). The study also found that the algorithm had assigned risk scores based on health expenditures accrued, which can be misleading if one group has substantially lower access and, thus, lower utilization and spending. Further, the study found that risk scores for black patients would more than double if biases were removed.

In an AI-driven HCO, the provision of equitable healthcare may very well depend upon the leaders' and developers' understanding of systemic disparities in diverse patient populations. A *Futurescan* survey of healthcare executives found that only 12% of health systems fully understand the profiles of their patient populations (2023). Understanding the patient population's economic, social, racial, and cultural backgrounds will be crucial in identifying algorithmic biases in future healthcare FMs.

Developing a Robust AI Governance Program

The *2023 Futurescan* survey results on healthcare trends indicate that 28% of health systems anticipate being prepared to adopt systemwide AI models by 2028 to manage care delivery. However, while the regulatory landscape of AI remains unclear, the responsibility falls on HCOs to establish a robust organizational governance structure to oversee the development and implementation of the technology. This essay is a call to promote the use of the governance framework illustrated in Fig. 3 in HCOs, based on the Hourglass Model of AI Governance by Mäntymäki et al. (2022). The model depicted has been slightly adjusted to accommodate the distinct characteristics of a health system. The model consists of three fundamental layers: environmental, organizational, and operational/AI system layer.

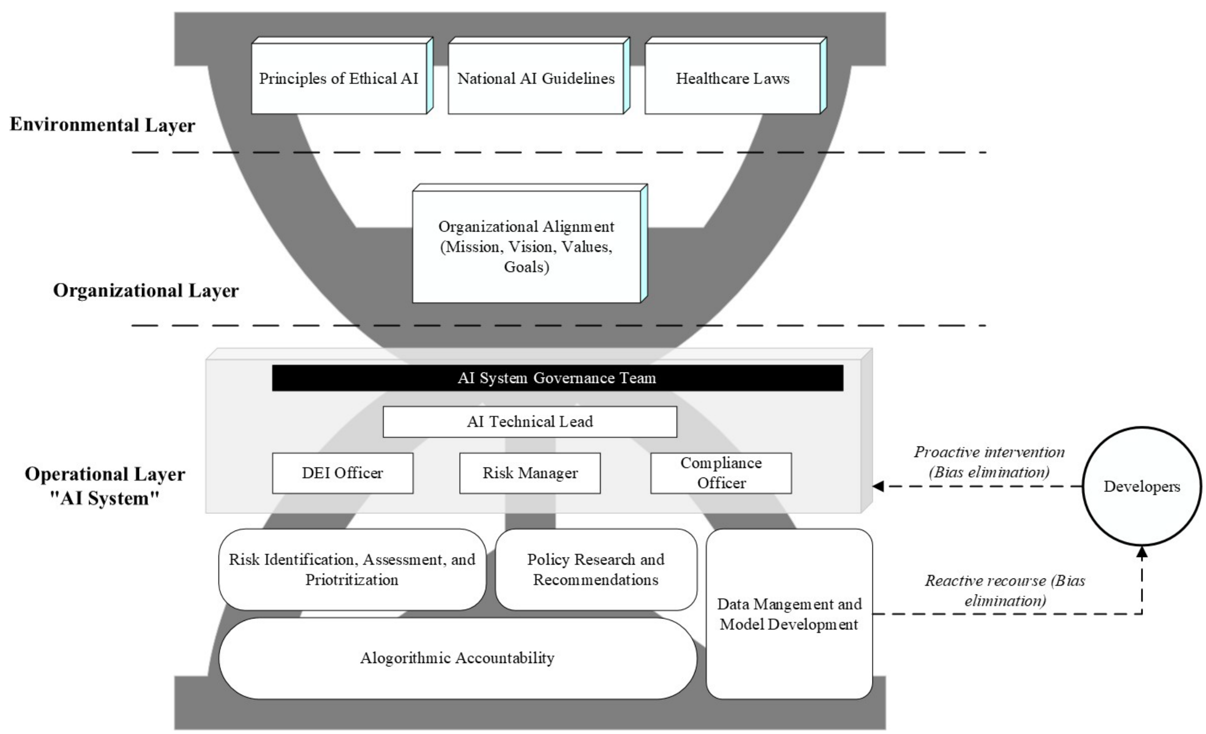

Fig. 3 FM Governance Structure

Environmental Layer

Mäntymäki et al. define this layer as an organization's 'contextual environment' (2022). Since there is no comprehensive legal framework for AI in the U.S., healthcare laws such as HIPAA constitute the most binding regulation within the environmental layer of an AI-driven HCO. This layer also encompasses the ethical principles of AI that will guide the organization. Without hard AI laws, having an ethical framework that clearly defines the appropriate and inappropriate use of the technology is highly crucial. Floridi and Cowls identified an overarching framework for ethical AI, incorporating the four traditional principles of bioethics (beneficence, non-maleficence, autonomy, and justice), along with the addition of a fifth principle: explicability. Explicability aims to comprehend and hold accountable the decision-making processes of an AI model (Floridi & Cowls, 2021).

Organizational Layer: Strategic Alignment

The organizational layer details the HCO's strategic AI initiative with a specific focus on the problem or opportunity that the technology is supposed to address. The strategic AI initiative must also align with the organization's mission, vision, values, and goals and include a specific plan with detailed timelines and meaningful success measures. This strategic alignment ensures that the AI system will perform according to its intended purpose.

Comprehensive Strategic Planning

This technological venture involves defining clear, actionable objectives accompanied by specific, measurable outcomes. Through a comprehensive needs assessment, the strategic team must construct a roadmap that is realistic and attainable, clearly identifying not only the "what" and "why" but also the "how" and "when" of AI deployment. The organizational layer must also foster cross-departmental collaboration to ensure AI initiatives are well integrated across all facets of the HCO, from clinical care to administrative functions, ensuring that AI tools are developed and implemented with a holistic view of the organization's needs, promoting synergies between departments and avoiding siloed efforts.

Operational Layer: The AI System

The operational layer or AI system is the bottom layer in the governance framework, which includes the core AI governance team. The governance team will be led by an AI executive, a leader who possesses specialized knowledge and expertise on the foundation model. In addition, officers or representatives from Risk Management, Compliance and Accreditation, and Diversity, Equity, and Inclusion (DEI) must comprise the rest of the core team. The core governance team will play a pivotal role in managing and monitoring the AI system throughout its lifecycle.

Core Operational Functions

The core governance team will oversee several key functions essential in the successful deployment and management of AI systems.

> **Risk Identification, Assessment, and Prioritization.** This involves continuous monitoring of potential risks that AI systems may pose in both clinical and non-clinical functions, from patient care to privacy and ethical concerns, and prioritizing them based on severity and likelihood.
>
> **Policy Research and Recommendations.** The core team will diligently monitor the changing landscape of AI guidelines, regulations, and best practices. The team will also be tasked with formulating policy recommendations that align with national standards and organizational objectives.
>
> **Algorithmic Accountability.** The team will ensure that the AI system operates transparently and accountably, with a mechanism in place to review and audit AI-driven decisions.

Developer Engagement

A critical aspect of the operational layer's functions is its interaction with AI developers. This two-way interaction involves working with developers to proactively identify and eliminate biases within the system before they impact patient care and operations. Should biases be detected post-implementation, the operational layer coordinates with developers to address and resolve these issues swiftly.

Conclusion

Foundation Models offer innovative solutions to longstanding healthcare problems in clinical and nonclinical functions, potentially optimizing an HCO's overall organizational performance. However, the understanding of this technology's potential impact on healthcare operations and patient care remains limited. Due to the lack of comprehensive regulatory oversight, HCOs must meticulously approach the adoption of FMs, which must be paired with a robust organizational governance structure and a core governance team to ensure trustworthy, ethical, and patient-centered AI use.

The risks addressed in the integration of FMs in healthcare primarily include privacy breaches, security vulnerabilities, model opacity, and algorithmic biases. These risks encompass the potential for unauthorized access to sensitive data, manipulation of AI systems by malicious actors, unexplainable decision-making processes, and the perpetuation of existing societal disparities through biased datasets and algorithms. Each of these risks significantly impacts patient safety, the trustworthiness of AI-enabled applications, and the ethical integrity of care delivery. To address these challenges, this essay advocates for the implementation of a multilayered governance model that collectively ensures a balanced and holistic governance approach.

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Mandatory Meals and Rest Periods for Texas Registered Nurses and Allied Health Professionals: A Brief on The Intersection of Research and Ethics

Anh Tuyet Le[1]

Abstract: Despite working in a mentally and physically challenging environment, no protection is defined in state or federal laws to mandate nutrition and rest periods for nurses and allied health professionals. This ethical dilemma puts nurses' health and patients' safety in jeopardy. If the nurse takes a break, it might prevent continuous, uninterrupted patient care. However, if the nurse does not take a break, she jeopardizes her health and the patient's safety. Similarly, allied health professionals have experienced the same conundrum. This brief will discuss research that supports mandatory nutrition and rest periods for Texas nurses and other healthcare workers to promote safety and wellness for themselves and their patients.

Introduction

Break laws are dependent on the individual state. In the United States (U.S.), 21 states and two territories defined the minimum length of the meal period, and nine states defined the minimum rest period for adult employees (U.S. Department of Labor [USDOL], 2023a & 2023b). However, no Texas labor laws exist on meals and rest periods for adults and minors. Hence, there is no required number or specified length of breaks for Texas Registered Nurses (RNs) who work long shifts, notably for 12-hour shifts or longer. With extended shifts without breaks, nurses experience physical and psychological issues that harm themselves, patients, families, employers, and the community (The National Institute for Occupational Safety and Health [NIOSH], 2020). As the third leading cause of death (Makary & Daniel, 2016), the economic impact of medical errors costs nearly $1 trillion annually using quality-adjusted life years, with preventable-medical-error-deaths being ten times the Institute of Medicine's statistics of 98,000 deaths annually in 1998 (Andel et al., 2012). The current reality represents a dilemma in ethics for nurses and patients in Texas. Consequently, Texas laws must explicitly define the minimum length and frequency of breaks during shift work for Texas Registered Nurses (R.N.s), protecting vulnerable patients' lives and providing Texas nurses and allied health professionals with much-needed breaks!

Personal Experience

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During my nursing career, I lost a patient once during a 12-turning 17-hour shift due to an unexpected surgical complication after prolonged cardiopulmonary resuscitation. With no break or relief, cough drops were my rescue to suppress hunger and thirst for nine consecutive hours. I was physically and emotionally exhausted. Internally, for my comfort, I interpreted the unusual water vapor patterns on my living room window as a farewell message from my late patient when I arrived home that night. While nursing has been my passion, my energy is depleted after those shifts. Although innumerable shifts without breaks and meals are typical throughout my career, I wonder about the future long-term consequences of the long work shifts without breaks on my physical and psychological health as well as my family's. In my experience, I have witnessed some, but countless untold tales from nurses and other healthcare workers were only shared privately with frustration and hopelessness in the locker rooms. Therefore, this brief on the intersection of research and ethics will elaborate on the lack of legal breaks and consequences, the driving factors for the changes, and the proposed strategy to resolve this long-overdue situation.

Literature Review

Lack of Lawful Breaks and Consequences

Despite their demanding roles in continuous and urgent patient care, including life and death circumstances on top of workplace violence, nurses have no legislative support in their requests for restorative breaks (Texas Health and Human Services [THHS], 2022). Subpar institutional policies, insufficient refreshing break areas in healthcare facilities, heavy workloads, unorganized workflows, and inadequate staffing are barriers to proper breaks (Nejati et al., 2016). In addition, the lack of state and federal regulations leaves the option to provide meals and rest periods at the discretion of individual employers. Federal laws dictate that meal breaks over 30 minutes need not be compensated, while rest periods under 20 minutes are paid (USDOL, 2023c). Additionally, disappointment in employers' policies, lack of political knowledge on labor rights, and lack of time and licit support hinder nurses' participation in health policy change (Safari et al., 2020). Due to fear of retaliation, dismissal, and punitive actions for speaking-up behaviors, nurses are hesitant to engage in whistleblowing about their working conditions (Mitchell, 2020).

Research shows that the lack of breaks caused increased occupational fatigue, poor dietary practices, self-injuries, medical errors, burnout, absenteeism, turnover, strikes, lawsuits, and deteriorated inter-professional and interpersonal relationships (Brown et al., 2018; Kelly et al., 2021). Similarly, a decrease in job satisfaction, overall health, performance, and resiliency has been noted (Horton Dias & Dawson, 2020; Nejati et al., 2016; Rutledge et al., 2022). These negative impacts on nurses, patients, the medical community, and healthcare institutions are likely to contribute to the current global emergency of nursing shortage. Inevitably, the image of overworked and injured nurses drastically reduces the profession's attractiveness to the younger generation and the public, which in turn further worsens the supply of R.N.s in Texas, with the shortage projection of a 57,012 RN deficit in 2032 (THHS, 2020).

The Driving Factors

Research shows that a supportive work environment for microbreaks decreases end-of-day fatigue and increases work engagement (Kim et al., 2022). On the other hand, the Tork survey of 1,600 North Americans shows that frequent and extended lunch breaks increased job satisfaction, retention, and recommendations of their companies (KRC Research, 2018). Despite break benefits, numerous Texas healthcare organizations have refused to compensate their nurses and allied healthcare workers for working through lunch breaks (see Appendix E). This negligence resulted in multiple lawsuits, as described by The Law Firm of Josh Borsellino, 2019 (Sixel, 2016a & 2016b). The risks associated with long work hours are decreased brain function, diminished job performance, increased medical errors, and short- and long-term health risks (NIOSH, 2020). Preventable harms of medical errors were the third leading cause of death (Makary & Daniel, 2016)., resulting in $19.5 billion of direct costs in 2008 in the U.S. (Andel et al., 2012). Their economic impact was estimated to be $1 trillion annually when quality-adjusted life years were applied. The patients shouldered $83 billion in indirect costs plus more than 70% of medical expenses associated with injuries and negligence through medical billings and malpractice claims (Bernazzani, 2015).

Furthermore, the workforce shortage delayed patient discharges and exacerbated hospital expenses ($135 billion) on top of the climbing labor costs ($86 billion) (American Hospital Association, 2022). The average annual cost of R.N. turnover is approximately $8.55 million, with an average hospital loss of $6.6-10.5 million in 2023. With an expected increase of 13.5% turnover, the hospital will have to spend more than $3 million for every 20 travel R.N.s hired for temporary replacements. However, a 1% reduction in R.N. turnover will save $400,000 annually (Nursing Solutions [NSI], 2023). So, what are the potential effective methods to combat these negative rates in human life and healthcare costs? One of the best solutions is enforcing Texas Fair Labor Laws that specify mandatory breaks for nurses and other allied healthcare providers.

The Strategic Solution

The following conditions are proposed to establish Texas Fair Labor (TFL) Laws for meals and rest periods for registered nurses and allies, addressing the current tragedy in Texas.

1) Shiftwork equal to or greater than 7.5 continuous hours daily requires a minimum of a 30-minute uninterrupted meal.

2) A second uninterrupted meal of at least 30 minutes is required for shiftwork equal to or greater than 11.5 continuous hours daily.

3) A net 15-consecutive-minute rest period is required for every four hours worked.

Finally, all parties must have a formal written agreement with specific details (see Appendix A). The proposed laws will ideally take the joined efforts between the three primary organizations, the Texas Workforce Commission (TWC), Texas Board of Nursing (TBON), Texas Nurses Association (TNA), and 26 other organizations to reduce the nursing shortage and advocate for R.N. break benefits (see Appendix C). The TBON will be granted the authority to support, monitor, enforce, and promote TFL law compliance in collaboration with other organizations.

In contrast to the current expenses for R.N. turnovers and hiring travel R.N.s for temporary coverage, the expenditure to cover nurses' breaks is minimal. Appendix B presents a detailed explanation of the cost. In brief, the proposed breaks will cost an average of $4.3 and $5.74 per patient daily for an 8-hour and 12-hour shift, respectively. In organizations with already scheduled breaks, adequate breaks for R.N.s to ensure optimal quality of care will only cost $2 or less per patient daily.

Benefits of the proposed Texas Fair Labor Law

With these proposed TFL laws, stakeholders can anticipate a sense of triumph and relief in various aspects of finance and wellness. Texas R.N.s and allies will achieve overall well-being with protected labor rights. The patients will get better access to a higher quality of care with the improvement of the nursing workforce. Plus, the patients can prospectively avoid the absorbed costs from medical billings and the indirect cost of hospital expenses. With higher nursing productivity, enhanced teamwork will reduce stress and increase job satisfaction for other allied healthcare professionals. The R.N.'s referrals and high regard for their healthcare institutions will facilitate workforce recruitment and potentially reduce hiring expenses. In addition, retention of current R.N.s will lessen the costs of turnover and travel staff employment while scoring higher on patient satisfaction with the safe nurse-patient ratio and skilled nursing staff familiar with the units' protocols. Ultimately, the Texas healthcare industry will have a brighter future with reduced medical costs due to preventable errors and labor shortages.

Conclusion

This brief proposes a bill for mandatory meals and rest periods for Texas R.N.s and allies. This bill will increase patients' safety and retain valued healthcare workers who provide outstanding care to our Texas community. The bill's passage will help protect the lives of vulnerable Texas patients and promote nurses' and allies' resiliency, especially during the aftermath of the COVID-19 pandemic. This brief intends to raise public awareness in hopes that the Texas legislature will pass Texas Fair Labor Laws to protect nurses and other healthcare workers and grant them their rightful breaks! Meals and rest periods are this most trusted profession's overdue fundamental rights to survive (Gallup, 2023). We need to preserve our essential workers so that the health and safety of Texas citizens can be ensured during daily life and sudden catastrophic events and epidemics.

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