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Viewpoint

Ethical Applications of Artificial Intelligence: Evidence From Health Research on Veterans

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Abstract

Background: Despite widespread agreement that artificial intelligence (AI) offers significant benefits for individuals and society at large, there are also serious challenges to overcome with respect to its governance. Recent policymaking has focused on establishing principles for the trustworthy use of AI. Adhering to these principles is especially important for ensuring that the development and application of AI raises economic and social welfare, including among vulnerable groups and veterans.

Objective: We explore the newly developed principles around trustworthy AI and how they can be readily applied at scale to vulnerable groups that are potentially less likely to benefit from technological advances.

Methods: Using the US Department of Veterans Affairs as a case study, we explore the principles of trustworthy AI that are of particular interest for vulnerable groups and veterans.

Results: We focus on three principles: (1) designing, developing, acquiring, and using AI so that the benefits of its use significantly outweigh the risks and the risks are assessed and managed; (2) ensuring that the application of AI occurs in well-defined domains and is accurate, effective, and fit for the intended purposes; and (3) ensuring that the operations and outcomes of AI applications are sufficiently interpretable and understandable by all subject matter experts, users, and others.

Conclusions: These principles and applications apply more generally to vulnerable groups, and adherence to them can allow the VA and other organizations to continue modernizing their technology governance, leveraging the gains of AI while simultaneously managing its risks.

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KEYWORDS
artificial intelligence; ethics; veterans; health data; technology; Veterans Affairs; health technology; data

Ethical Applications of Artificial Intelligence in Veterans' Health Research

There is increasing recognition that artificial intelligence (AI) offers significant potential to help or harm the world. Much like other technologies, ranging from the internet to computers, AI is neither bad nor good: the impact of AI depends on how its users wield it. Already, there is an emerging body of AI use cases in health care [1,2], including for vulnerable groups and veterans [3], that are increasingly originating from populations the federal government considers to be "potentially vulnerable patient populations" [4]. These groups can be especially sensitive to adoption of technology; therefore, additional scrutiny is required around the ethical underpinnings and likely causal effects on these groups. In this sense, the question is not whether the federal government should engage AI for broader social benefit, but how it can do so using a values-based framework to guide AI applications and their continued research and development.

At least since the publication of the Belmont Report [5], there has been general recognition in the federal government of three principles that guide the introduction of new technologies to this day. First, *respect for persons* details that individual autonomy and privacy must be protected. Second, *beneficence* states that technologies should be designed to maximize the potential net benefits to society, safeguarding against potential harms and long-term consequences. Third, *justice* ensures that there are equitable benefits from research. That is, when individual data is collected, it must be used to benefit those individuals. Although the Belmont Report focused on biomedical technologies, they exhibit many similarities with AI, particularly in terms of their ethical implications and long-lasting impacts.

The primary contribution of this commentary is to explore the ethical applications of AI by building on the Belmont Report and relating it with the principles established in the recent executive order on trustworthy AI. Although there has been a recognition of data ethics and privacy within the US federal government, a new challenge has emerged: how can the federal government balance between the competing priorities of stewarding sensitive data and using AI to analyze it to drive veteran outcomes?

To answer this question, we apply the perspective of the Veterans Health Administration, within the Department of Veterans Affairs (VA), which has the largest integrated health care system in the United States and has pioneered several technological aspects now widely seen in this country, such as electronic health records (EHRs). Additionally, more than half of physicians training within the United States receive some training at a VA medical center. By evaluating uses for AI and implications in health care, veteran input and priorities can be proactively developed to enhance care. For example, the VA is already using AI to facilitate early detection of cancer [3], detection of acute kidney injury [6], and prediction of loneliness and declines in mental health [7,8]. These examples all highlight the ways that AI can be used to advance patient outcomes; however, they also point toward data privacy and trust considerations.

The recent executive order, "Promoting the Use of Trustworthy Artificial Intelligence in Government" [9], provides a framework for the VA to move forward with using AI to improve veteran health on a larger and more systematic scale. We focus on three principles that are especially relevant to the advancement of the health and well-being of veterans: (1) purposeful and performance-driven; (2) accurate, reliable, and effective; and (3) understandable.

1. Purposeful and Performance Driven

> *…seek opportunities for designing, developing, acquiring, and using AI, where the benefits of use significantly outweigh the risks and the risks are assessed and managed* [9]

The VA is working to employ AI in high priority areas where there is robust opportunity to advance veteran health outcomes. Recent work indicates that difficulty in transitioning to civilian life is a critical factor underlying negative mental health outcomes in veterans. For example, Makridis and Hirsch [10] have documented a deterioration in labor market outcomes among veterans over the past decade, showing that veterans are increasingly concentrated in metropolitan areas with lower wage and employment growth. Moreover, Makridis et al [11] show that socioeconomic factors are the largest predictors of mental health outcomes among veterans, dwarfing the contribution of location and demographic-specific features. Intuitively, because a significant amount of time is allocated toward work activities, the absence of purpose and self-efficacy in the workplace, especially after coming from a mission-driven environment in the armed services, will impact veterans' mental health.

AI can be part of the solution. To the extent that veteran records from combat are combined with self-assessments of skills and career preferences, and these data could be comprehensively gathered and harmonized, researchers could use methods from AI to provide veterans with personalized recommendations regarding not only potential job fits but also counseling over the course of their careers. One of the sources of low engagement among employees is a feeling of plateauing and helplessness; therefore, AI-driven recommendations regarding how to optimize career mobility and human capital development would provide veterans with actionable steps to continuously acquire and apply new skills at work.

Another prime example involves personalizing feedback to veterans about how to live healthier lives. End-of-life care is one of the largest sources of health care expenditures. For example, Riley and Lubitz [12] estimate that a quarter of all Medicare spending goes toward care for people during their last year of life. These resources could be more impactful if they were allocated more toward preventative care earlier in life. Using deep learning methods, Ahadi et al [13] illustrate how biological data can be used for longitudinal profiling. Implementing this algorithm, combined with EHRs at the VA, offers the potential to provide practical advice about how to live more productive and happier lives, raising both economic and social well-being.

Veterans in rural areas face challenges accessing care due to a paucity of rural treatment facilities. AI, implemented along with smart devices (eg, smart wearables), could allow for remote monitoring of rural veterans' health and enable smart devices to alert veterans of health concerns. Recent evidence indicates that AI may be able to predict a person's mental state, including the likelihood of suicide, raising the likelihood that smart devices could be used for predicting and intervening in veteran suicide [7,8].

However, the benefits of AI depend on ethical implementation. Risks associated with AI implementation need to be thoroughly assessed and managed. If, for example, privacy is disrespected, public trust and confidence, particularly among those who have already sacrificed so much for their country, would be undermined. This is extremely important at the VA, where sensitive data, which is under continuous reassessment and review, is routinely collected from veterans. Moreover, researchers must be cognizant of the potential for replicating sources of bias when training their AI algorithms. That is, researchers must investigate the data and model to, at least qualitatively, assess whether there are potential biases that could lead to error replication through the AI-driven recommendations. For example, one possibility is that samples are not representative of the entire population of veterans [14], particularly those who do not feel comfortable using technology. Researchers must also ensure that AI-driven insights are derived from representative samples that reflect the diversity of experiences, attitudes, ethnic, and gender composition among veterans. Recent evidence, for example, highlights the lack of diversity in many health care databases as a major limitation [15].

2. Accurate, Reliable, and Effective

> *…ensure that their application of AI occurs in well-defined domains, and is accurate, reliable, effective, and fit for intended purposes* [9]

The VA is well-equipped to ensure the accuracy, reliability, and effectiveness of AI applications in health and well-being. The VA has collected and catalogued over two petabytes of data, including data on veteran health, prescription data, and inpatient and outpatient services, among others. Further, the VA established the Million Veteran Program, which characterizes, through a consented cohort of subjects, the confluence of genes, lifestyle, and military exposure on veteran health outcomes. This breadth of data paves the way for algorithms that promote personalized medicine based upon life experience and genetic factors. In particular, the plethora of data at the VA can be leveraged to train high-quality algorithms to serve veteran needs.

Concerns have been raised over whether AI algorithms will be effective and generalize beyond the training set originally used to develop machine learning (ML) algorithms [14]. Importantly, the VA's data sets are generated from VA centers across the country and, in principle, data should accurately capture the diverse spectrum of veterans. Therefore, AI algorithms trained on these data should prove to be reliable even when implemented in varied VA centers throughout the United States. However, cautious implementation and monitoring is necessary to ensure that each developed AI algorithm is beneficial at VA centers.

Although the VA database spans millions of veterans, there are still many veterans who are not included in the system. For example, homelessness is a large challenge for the veteran population, and if these veterans are not included within the VA system, they cannot receive the available benefits and treatment [16]. Our internal calculations from the American Community Survey conducted by the Census Bureau suggest that there are roughly 18 million veterans in the United States, whereas the VA only covers roughly 9 million of them [17]. To ensure that AI applications produce reliable recommendations for all veterans, it is important to ensure that the data being fed into predictive models is representative.

In addition to the importance of maintaining a representative sample, researchers and clinicians must use appropriate AI techniques. One particularly large challenge with clinical decision support tools and the use of electronic health records is the presence of missing data and small sample sizes. While sample size is less of a challenge within the VA because of the size of its EHR database, missing data can be a source of bias if they are not missing at random [18]. Some ML techniques, such as gradient boosting and decision trees, can deal well with missing data; however, researchers need to be careful about applying ML and automation in these environments. There is also a well-known bias that can emerge against specific groups, whether by race or even socioeconomic status, which can be propagated at scale if ML algorithmics are not trained and "de-biased" properly [19]. However, it is becoming clear that researchers developing predictive models for clinical use need to transcend traditional conversations about algorithmic bias and think harder about the broader and structural forces that are at play in the observed phenomena [20].

3. Understandable

> *…ensure the operations and outcomes of their AI applications are sufficiently interpretable and understandable by subject matter experts, users, and others as appropriate* [9]

A concern for AI development is the necessity for algorithms to be explainable. Explainability is the concept that users should be able to understand how algorithms function, and it is conceptualized along a continuum where relatively simple algorithms based upon branching decision trees and linear regression are feasible to understand [21]. However, the use of deep neural networks (DNNs), where decision-making is spread across multiple layers of interconnected decision-making nodes, currently produces results that are difficult to accurately interpret. Although DNNs provide great utility in analyzing complex data sets, there is concern over the "black box" nature of DNNs, although new methods are being developed to provide explainability to DNNs [22]. Explainable algorithms will foster trust in AI by both clinicians and patients at the VA.

These new principles for the promotion of trustworthy AI build upon an existing framework developed in the VA, Ethical Principles for Access to and Use of Veteran Data [23], that safeguards veterans and their data and ensures that veterans benefit from research. In other words, research is not an end in and of itself—it is a means toward delivering value to veterans. Moreover, these principles are rooted in the legacy of the Belmont Report from 1979 [5], which emphasized privacy, beneficence, and justice in applications of technology. At its root, technology exists to help improve well-being, whether through heightened productivity or quality of the services provided. Together, these principles provide a signpost for clinicians and researchers to work collaboratively so that AI is developed and deployed for social good, especially for vulnerable groups and veterans.

Moreover, these ethical principles developed and operationalized within the VA can be extended across the broader health care sector. For example, large university hospital systems that exist within the research ecosystem can adopt these ethical principles to guide their strategic investments and the development and deployment of AI tools. In fact, these university ecosystems have many similarities to the VA because they bring together a combination of researchers and clinicians under a common umbrella and institutional resources. Researchers and clinicians can work hand-in-hand to ensure that research and development investments are fundamentally driven by areas of great need and potential impact.

These processes for the development and application of ethical AI extend beyond veterans. In particular, members of any vulnerable group are beneficiaries of adherence to these processes because, by definition, they may find it harder to benefit from AI. For example, while AI is also leading to the invention of new jobs and tasks in the labor market, AI also reduces the demand for other skills that are more routine and manual, which may affect veterans more if they are concentrated in those types of jobs and occupations. In this sense, applications of AI aimed at improving the transition of service members into the civilian sector could not only help veterans directly by, for example, providing them with tools to more efficiently match into jobs that suit their preferences and abilities, but could also improve trust and confidence in the benefits of AI. Moreover, other vulnerable groups likely face similar challenges; therefore, processes for the development and application of AI would help them too.

Our paper explains some of the most important ingredients for ensuring that AI advances are applied in ways that promote improved veteran outcomes. Furthermore, the VA could serve as a model organization, protecting VA patient data and leveraging it for their good and ultimately cutting health care costs, increasing efficiency, and enhancing health care for veterans. If the United States can successfully scale AI under a technology governance structure using these principles, the possibilities are limitless.

Conflicts of Interest

None declared.

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Abbreviations

AI: artificial intelligence
DNN: deep neural network
EHR: electronic health record
ML: machine learning
VA: Department of Veterans Affairs

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Original Paper

Unsupervised Machine Learning for Identifying Challenging Behavior Profiles to Explore Cluster-Based Treatment Efficacy in Children With Autism Spectrum Disorder: Retrospective Data Analysis Study

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Abstract

Background: Challenging behaviors are prevalent among individuals with autism spectrum disorder; however, research exploring the impact of challenging behaviors on treatment response is lacking.

Objective: The purpose of this study was to identify types of autism spectrum disorder based on engagement in different challenging behaviors and evaluate differences in treatment response between groups.

Methods: Retrospective data on challenging behaviors and treatment progress for 854 children with autism spectrum disorder were analyzed. Participants were clustered based on 8 observed challenging behaviors using *k* means, and multiple linear regression was performed to test interactions between skill mastery and treatment hours, cluster assignment, and gender.

Results: Seven clusters were identified, which demonstrated a single dominant challenging behavior. For some clusters, significant differences in treatment response were found. Specifically, a cluster characterized by low levels of stereotypy was found to have significantly higher levels of skill mastery than clusters characterized by self-injurious behavior and aggression (P<.003).

Conclusions: These findings have implications on the treatment of individuals with autism spectrum disorder. Self-injurious behavior and aggression were prevalent among participants with the worst treatment response, thus interventions targeting these challenging behaviors may be worth prioritizing. Furthermore, the use of unsupervised machine learning models to identify types of autism spectrum disorder shows promise.

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KEYWORDS

autism spectrum disorder; challenging behaviors; unsupervised machine learning; subtypes; treatment response; autism; treatment; behavior; machine learning; impact; efficacy; disorder; engagement; retrospective

Introduction

Autism spectrum disorder is a neurodevelopmental disorder characterized by deficits in social communication and social interaction, as well as the presence of restricted, repetitive patterns of behavior, interests, and activities [1]. With the exception of restricted, repetitive behaviors (eg, stereotypy, perseveration), challenging behaviors are not classified as a core symptom of autism spectrum disorder; however, these behaviors are prevalent among individuals with autism spectrum disorder. As many as 94% of children with autism spectrum disorder engage in some type of challenging behavior, often including stereotypy (eg, self-stimulatory or persistent repetitive motor or vocal behavior), aggression, tantrums, and self-injurious behavior [2,3]. Challenging behaviors may pose risk of injury to the individual or others and may inhibit learning opportunities and social interactions [4]. Furthermore, challenging behaviors may negatively impact family functioning and contribute to caregiver stress [5,6].

Various risk factors for engagement in challenging behaviors have been investigated in individuals with autism spectrum disorder. Symptom severity has been found to predict challenging behaviors, with greater symptom severity associated with engagement in higher numbers of challenging behaviors at stronger intensities [2,3]. Intellectual functioning has also been linked to challenging behaviors in individuals with autism spectrum disorder, with greater deficits in intellectual functioning predicting greater frequencies of stereotypy [7,8], aggression [8], and self-injurious behavior [8,9]. In addition, deficits in adaptive skills [10,11] and expressive language skills [11] have been associated with engagement in challenging behaviors in individuals with autism spectrum disorder, but studies [8-12] that investigated the relationship between gender and challenging behaviors found no significant differences in engagement in challenging behaviors between boys and girls with autism spectrum disorder.

Applied behavior analysis interventions, which involve the application of principles and procedures of learning and motivation to alter behavior [13,14], may be used to reduce challenging behaviors and increase appropriate behaviors in individuals with autism spectrum disorder. Specific challenging behaviors that are commonly addressed in treatment include stereotypy, noncompliance, and aggression [15]. Outcome studies for children with autism spectrum disorder have not often included challenging behaviors as an outcome measure [4,16]. Several group design studies [17-19] have found evidence to support the use of caregiver training to manage challenging behaviors. Furthermore, there is an abundance of single-individual research evaluating the effectiveness of behavioral interventions for challenging behaviors in individuals with autism spectrum disorder, and reviews of this research have found behavioral interventions, particularly those implementing pretreatment functional assessments, to be effective in reducing challenging behaviors [20-22].

Applied behavior analysis–based therapy is considered to be well-established for the treatment of autism spectrum disorder [23,24]. While ample research demonstrates the effectiveness of applied behavior analysis–based treatment [25,26] research also reveals variability in individual response to treatment [27,28]. Treatment-related variables including greater treatment intensity [27,29-32], longer treatment duration [30-32], and greater total intervention time [33,34] have been linked to superior treatment outcomes. Furthermore, many patient-related variables have been associated with greater treatment gains. These include younger age [29,32,34-38], lower autism spectrum disorder symptom severity [35,36,38,39], and greater intellectual functioning [27,36,38-45].

Research evaluating the impact of challenging behaviors on treatment response in individuals with autism spectrum disorder is limited. Eikeseth and colleagues [46] investigated whether challenging behaviors, among other intake measures, were associated with treatment outcomes for adaptive behavior and autism spectrum disorder symptoms in children with autism spectrum disorder; however, challenging behaviors were not found to be a predictor of treatment outcome. Conversely, Remington and colleagues [39] found that higher rates of challenging behaviors at intake were associated with superior response to treatment and suggested that their counterintuitive findings may possibly be attributed to the sensitivity of the measure used to assess challenging behaviors. Given the prevalence of challenging behaviors among individuals with autism spectrum disorder, additional research is needed to investigate the impact of these behaviors on treatment response.

To account for the heterogeneity observed across individuals with autism spectrum disorder, researchers have investigated types of autism spectrum disorder [47]. Preliminary research has found behavioral types of autism spectrum disorder to have differences in gene expression [48-50], developmental trajectory [51-54], and treatment response [55]. In a recent study, Stevens and colleagues [55] used an unsupervised machine learning model to identify behavioral types of autism spectrum disorder and evaluate differences in treatment response across types. Participants included 2400 children with autism spectrum disorder. Data from a comprehensive assessment of skill deficits and treatment progress data were analyzed. A total of 16 autism spectrum disorder groups were identified using a Gaussian mixture model. Using a linear regression model, relationships between treatment hours and skill mastery were found to be strong within groups, accounting for 64% to 75% of variance. These findings are a preliminary step toward advancing targeted treatments and improving outcomes for individuals with autism spectrum disorder based on type membership.

Autism spectrum disorder types may also be identified based upon profiles of challenging behavior. Stevens and colleagues [56] conducted an analysis of challenging behaviors in a large sample of children with autism spectrum disorder (n=2116). Using *k*-means clustering, 8 diverse profiles, in which a single dominant challenging behavior was apparent, were identified. Furthermore, gender differences were observed when cluster analyses were performed separately for male and female participants. While all of the male clusters were found to exhibit a single dominant challenging behavior, 2 of the female clusters indicated equal engagement in 2 dominant challenging behaviors. These findings suggest that gender may play a role in the presentation of challenging behaviors in individuals with autism spectrum disorder. Further investigations into autism spectrum disorder types based on challenging behaviors are warranted.

The study of challenging behaviors across types of autism spectrum disorder may help explain some of the variation observed in treatment outcomes across individuals with autism spectrum disorder and may advance efforts to develop targeted treatments to maximize outcomes. Preliminary evidence indicates there are autism spectrum disorder types based on challenging behaviors; however, little is known about how challenging behaviors impact treatment response. The purpose of this study was to identify types of autism spectrum disorder based on engagement in different challenging behaviors and evaluate differences in treatment response between groups and across gender.

Methods

Data Set

Deidentified retrospective treatment data for a large sample of children with autism spectrum disorder were used in this study. Data on the frequency of challenging behaviors and treatment progress were obtained from the Skills system software (Skills Global LLC [57]). Skills includes a thorough assessment of skill deficits with demonstrated reliability [58] and validity [59], a comprehensive curriculum to build individualized treatment plans, and tracking capabilities for challenging behaviors and ongoing treatment progress. In addition to Skills data, operational data on treatment hours were used in this study.

Participants included children with autism spectrum disorder who were receiving applied behavior analysis treatment from a community-based provider. A total of 2116 clinical records were reviewed based on the following inclusion criteria: (1) were between the ages 18 months and 12 years old; (2) had a diagnosis of autism spectrum disorder, autistic disorder, pervasive developmental disorder–not otherwise specified, or Asperger syndrome by an independent licensed clinician (eg, psychologist, pediatrician, etc); (3) received at least 20 hours of treatment per month; and (4) had at least 1 month of continuous services; (5) demonstrated repeated instances of challenging behavior as documented in their treatment history; and (6) had available treatment response data over the course of treatment. Parameters with respect to age were set based on the age range predominately represented in the data set to avoid potential outliers that may have affected the cluster analysis. Likewise, parameters regarding treatment intensity and duration were established so that each participant had adequate treatment response data to include in the analysis. After applying these criteria, a sample of 854 participants were included. Of the participants, 706 were male and 148 were female. The average age of participants was 7.59 (SD 2.17) years old, ranging from 2.74 years to 12 years. Participants resided in the states of Arizona, California, Colorado, Illinois, Louisiana, New York, Texas, and Virginia. The data used for this study were collected during a 36-month period (January 1, 2014 through December 31, 2016).

Measures

Data on engagement in challenging behaviors were used to identify potential clusters. While the classification of challenging behaviors is subjective in nature, there is agreement among the literature regarding operational definitions for common topographies of challenging behaviors exhibited by individuals with autism spectrum disorder [4]. While this may not be exhaustive, data were examined for the following topographies of challenging behaviors: aggression (eg, hitting, kicking), disruption (eg, interrupting, yelling), elopement (eg, wandering, bolting), noncompliance (eg, defiant behavior, refusing), obsessive behavior (eg, repeatedly talking about the same topic, preservation), self-injurious behavior (eg, head banging, hand biting), stereotypy (eg, hand flapping, toe walking, vocal stereotypy), and tantrums (eg, crying, falling). Skills is implemented as a relational database, which allows behavior interventionists to record observations in real time during a therapy session using an iPad and the corresponding Skills app. In the case of challenging behaviors, when such a behavior is observed, the therapist marks the type of behavior and provides a textual description of its context. This information is then timestamped and then stored in the underlying relational database. Aggregation of challenging behavior data for each patient can then be easily achieved using a simple database query (SQL format). An extra validation step was taken to compare identified challenging behaviors to the textual description provided by the behavior interventionist to ensure no challenging behavior observations were misidentified.

Data on mastered learning objectives were used to evaluate treatment response. Mastery criteria for learning objectives were determined by the patient's clinician and individualized to the patient. Typically, mastery was defined as 80% accuracy or greater for a minimum of 2 treatment sessions across 2 days.

Treatment

Participants received individualized applied behavior analysis–based treatment. Treatment comprehensively targeted deficits across developmental domains, including language, social, adaptive, cognitive, executive function, academic, play, and motor skills. Services were provided in the participant's home, clinic, school, community, or a variety of settings. Treatment was provided according to the Center for Autism and Related Disorders model [60].

Participants' treatment programs addressed skill acquisition and targeted the reduction of challenging behaviors. Interventions for challenging behaviors varied based on the target behavior's topography and function (determined using functional assessment). Possible interventions implemented by a participant's clinician included: antecedent-based interventions (ie, manipulations to the environment to reduce the target behavior) such as noncontingent reinforcement, demand fading, task modification, and choice; replacement behavior interventions including functional communication training, differential reinforcement of alternative behavior, and differential reinforcement of incompatible behavior; and consequence-based interventions (ie, manipulations to the events following the target behavior to reduce the likelihood of its reoccurrence) such as extinction, differential reinforcement of other behavior, differential reinforcement of low rate behavior, and response interruption and redirection.

Data Analysis

Clustering

This analysis expanded on the work of Stevens and colleagues [56] to explore differences in treatment response across identified challenging behavior clusters in individuals with autism spectrum disorder. Patients were clustered based on relative frequency of 8 challenging behaviors (aggression, disruption, elopement, noncompliance, obsessive behavior, self-injurious behavior, stereotypy, and tantrums) using a *k*-means machine learning algorithm. This was achieved by creating an 8-dimensional feature vector for each patient. Relative frequency was calculated by finding the proportion of all challenging behaviors for each of the 8 categories for each patient. Duration and severity of the challenging behaviors were not taken into consideration for this value. Each vector element corresponded to the relative frequency of a specific challenging behavior observed for that patient. The 8-dimensional vectors were fed directly to the clustering algorithm without the use of feature selection because the dimensionality of the data was relatively small, and it was important to preserve each of the challenging behaviors in the final cluster model. Once clusters were identified using the *k*-means algorithm, multiple linear regression was performed to evaluate interactions between cluster assignment, treatment response, and gender.

The goal of clustering is to find latent groups, or clusters, in data. Patients within the same cluster will have more similar challenging behaviors profiles than patients in different clusters [61]. The *k*-means methods was selected for clustering because it is computationally efficient, easily implemented, and is a widely used prototype-based clustering algorithm, wherein each cluster is represented by a prototype. This prototype can either be the centroid of data points with similar continuous features or the medoid in the case of categorical features. This data set involved continuous features; therefore, each cluster had a centroid.

The *k*-means algorithm was implemented with 5 steps. (1) The best value of *k* (ie, the number of clusters) was identified by incrementally testing values between 2 and 20. (2) For each of these values, the algorithm picked *k* sample points from the data at random, which are the initial centroids (c_1, c_2, ..., c_k). (3) Each 8-dimensional data point d_i was assigned to the nearest centroid c_k using Euclidean distance to measure the distance between the point and the centroid. (4) The algorithm recalculated the centroids by taking the mean value (for each behavior) from all the data points currently in the cluster. (5) The algorithm repeated steps 3 and 4 until the cluster assignments did not change or a maximum number of iterations was reached.

To find the distance between the data points and the centroids in the data set, squared Euclidean distance was used. Similarity between data points is defined as the opposite of distance. A commonly used metric for finding the distance between data points *x* and *y* in *m*-dimensional space is the squared Euclidean distance.

Once similarities are measured, clustering becomes an optimization problem. An iterative approach was used to minimize the within-cluster sum of squared errors or cluster inertia. Once these errors were calculated, a graph of the errors were examined using the elbow method to find the best value for *k*. The elbow method involves examining the plot (ie, the arm) to determine the point at which diminishing returns are observed (ie, the elbow). As *k* increases, the sum of squared errors gets smaller. When *k* is equal to the number of points in the data set, the sum of squared errors is 0 and every point is its own cluster. Choosing *k* to correspond to the elbow in the graph thus provides an effective measure by which to prevent overfitting. The chosen *k* indicates the optimal number of clusters that are both cohesive and separate.

Linear Regression

A multiple linear regression model was used to evaluate the relationships between the target variable (skill mastery) and explanatory variables (treatment intensity, cluster assignment, and gender).

In univariate linear regression, the relationship between a single explanatory variable *x* and a response or target variable *y* is modeled. The equation used for linear models with only 1 predictor variable is defined as $y_i=\beta_0+ \beta_1 x_i+\varepsilon_i$, where the weight β_0 represents the *y*-axis intercept and β_1 is the coefficient of the explanatory variable. In simple linear regression, the goal is to find the weights of the equation to explain the relationship between the explanatory variable and the target variable. From this, the responses of new data points that were not part of the observed data may be predicted and coefficients of the model may be interpreted. The simple linear regression equation may be generalized to produce an equation for multiple linear regression that involves multiple explanatory variables.

Linear regression works by taking the explanatory variables and the response variable, and fitting a straight hyperplane to the data that minimizes the distance between an observed point and the fitted model. The explanatory variables were treatment intensity, cluster assignment, and gender, and the response variable was skill mastery.

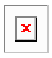
An efficient way to quantitatively measure a model's performance is the mean squared error, which measures the average squared error between the model’s prediction and the actual values. Mean squared error may be used to compare different regression models with the same outcome.

R^2 (another measure of model fit) is bounded between 0 and 1, with 1 indicating a perfect relationship between *x* and *y* and mean squared error is equal to 0. *R* allows for the specification of interaction terms in regression formulas. An interaction occurs when the product of 2 predictor variables is also a significant predictor [62]. In this study, there were 3 explanatory variables (treatment intensity, cluster assignment, and gender), and all interactions were included in the model.

Tukey Posthoc

Results from the regression model indicated that there was a significant difference between treatment hours, cluster assignment, and the interaction between cluster assignment and gender. Posthoc analysis was conducted to determine which pairs of clusters significantly differed. The Tukey honestly significant difference method was used to correct for multiple comparisons.

The Tukey posthoc test assesses all the pairwise comparisons using the Tukey honestly significant difference formula



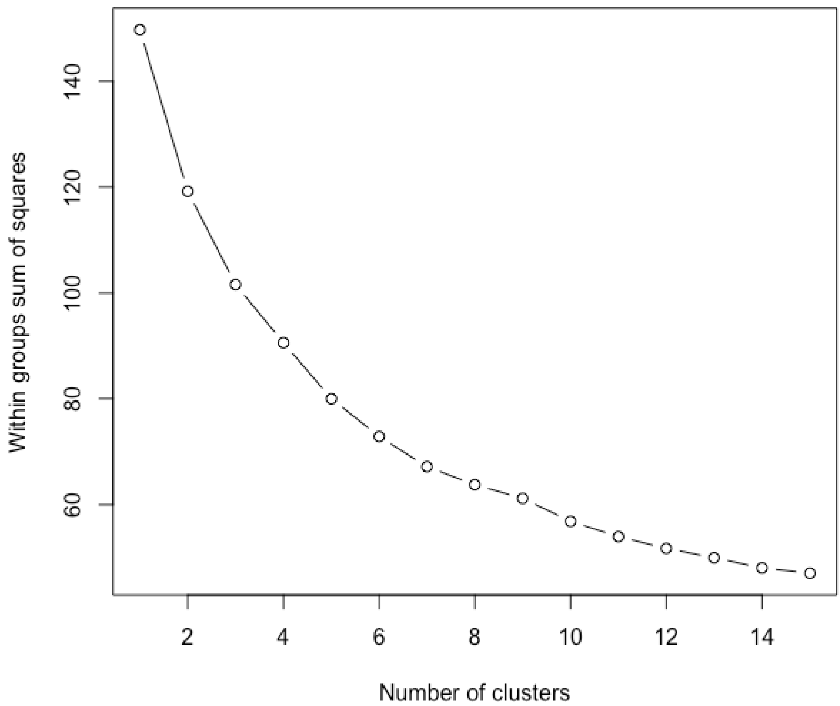
where $M_i - M_j$ is the difference between the pairs of means, MS_w is the mean square within, and n is the number of clusters.

Results

Clustering

Figure 1 shows within-group sum of squared errors for patients. The optimal value of *k* (the number of distinct challenging behavior profiles) was found to be 7, confirmed both by the elbow method and by silhouette score (the highest indicates most cohesive and separate). Each cluster corresponds to a phenotype and can be quantitatively represented with its centroid (the mean relative frequency for each of the 8 challenging behaviors for patients in that cluster). The dimensionality of each centroid is identical to the input feature space, which is preserved during the clustering process.

Figure 1. Within-cluster sum of squared errors for all patients, both male and female. The elbow method indicates that the best value of *k* is 7, meaning there are 7 clusters.



Seven phenotypes of autism spectrum disorder, most of which demonstrated 1 dominant challenging behavior, were identified based on average frequency (centroid) of 8 challenging behaviors (ie, aggression, disruption, elopement, noncompliance, obsessive behavior, self-injurious behavior, stereotypy, and tantrums) calculated for each cluster (Table 1). It is important to reiterate that the machine learning process is unsupervised. The phenotypes are identified by the algorithm without the need for human labels, which are required for supervised learning (classification).

Table 1. Breakdown of identified clusters.

Cluster	Dominant challenging behavior	Boys, n	Girls, n	All, n
1	Tantrums	60	14	74
2	Self-injurious behavior	79	8	87
3	Elopement	78	18	96
4	Stereotypy (low rate)	170	37	207
5	Noncompliance	87	26	113
6	Aggression	113	26	139
7	Stereotypy (high rate)	119	19	138

The radar graphs shown in Figure 2 and Figure 3 provide visual representations of each phenotype's engagement in the 8 challenging behaviors. The radar charts in Figure 3 were scaled from 0 to the average frequency of the dominant challenging behavior. For example, Cluster 1 was scaled from 0 to 0.6, to which tantrums extend. Cluster 4 was scaled from 0 to 0.4, to which stereotypy extends. It is worth noting that Cluster 4 and Cluster 7 both have stereotypy as their dominant challenging behavior, but their frequencies were different. Cluster 4 was found to engage in stereotypy at a lower rate than Cluster 7.

Figure 2. Radar graphs depicting engagement in challenging behaviors across clusters.

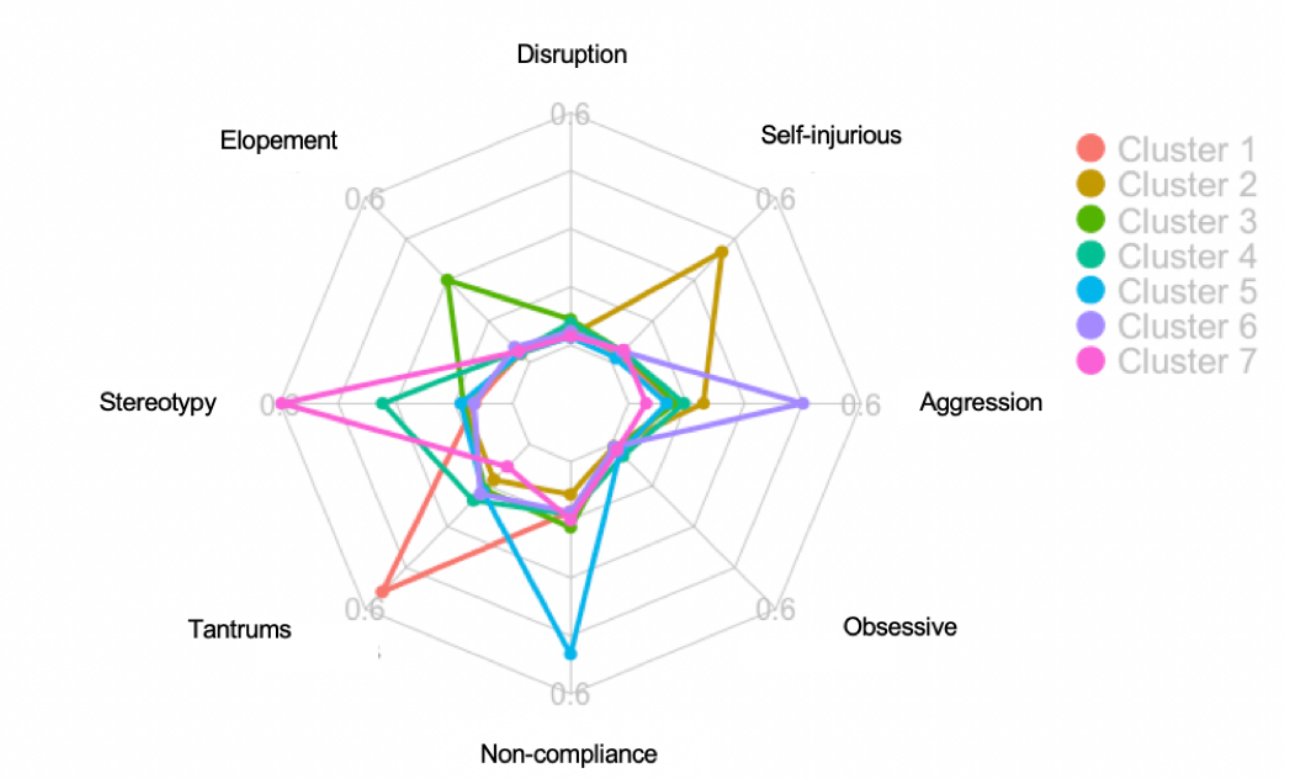


Figure 3. Radar graphs showing the dominant challenging behavior for each cluster. Note that the maximum varies between the clusters, particularly Cluster 4 and Cluster 7, in which patients demonstrate the same dominant challenging behavior.

Linear Regression

The R^2 value was found to be 0.67. The value for R^2 is the fraction of the variance of exemplar mastery that is explained by the model. Thus, the model explained 67% of the variance of exemplar mastery. The model was significantly predictive of mastery ($F_{27,826}$=61.05, P<.001).

Figure 4 shows the regression lines for male and female patients in each of the different clusters. The mean squared error for each cluster is shown in Table 2.

Figure 4. The line of best fit for each gender and cluster.

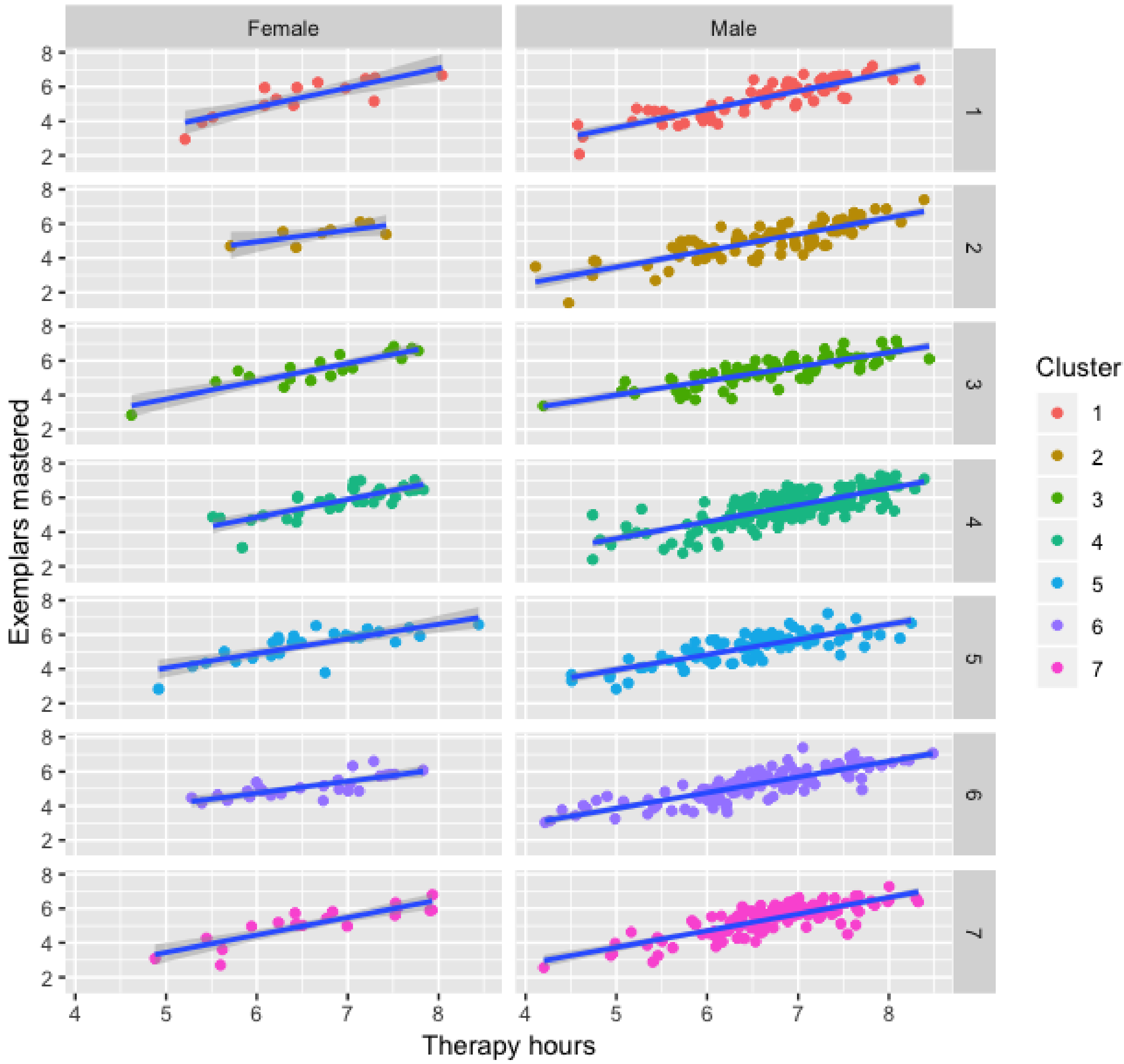
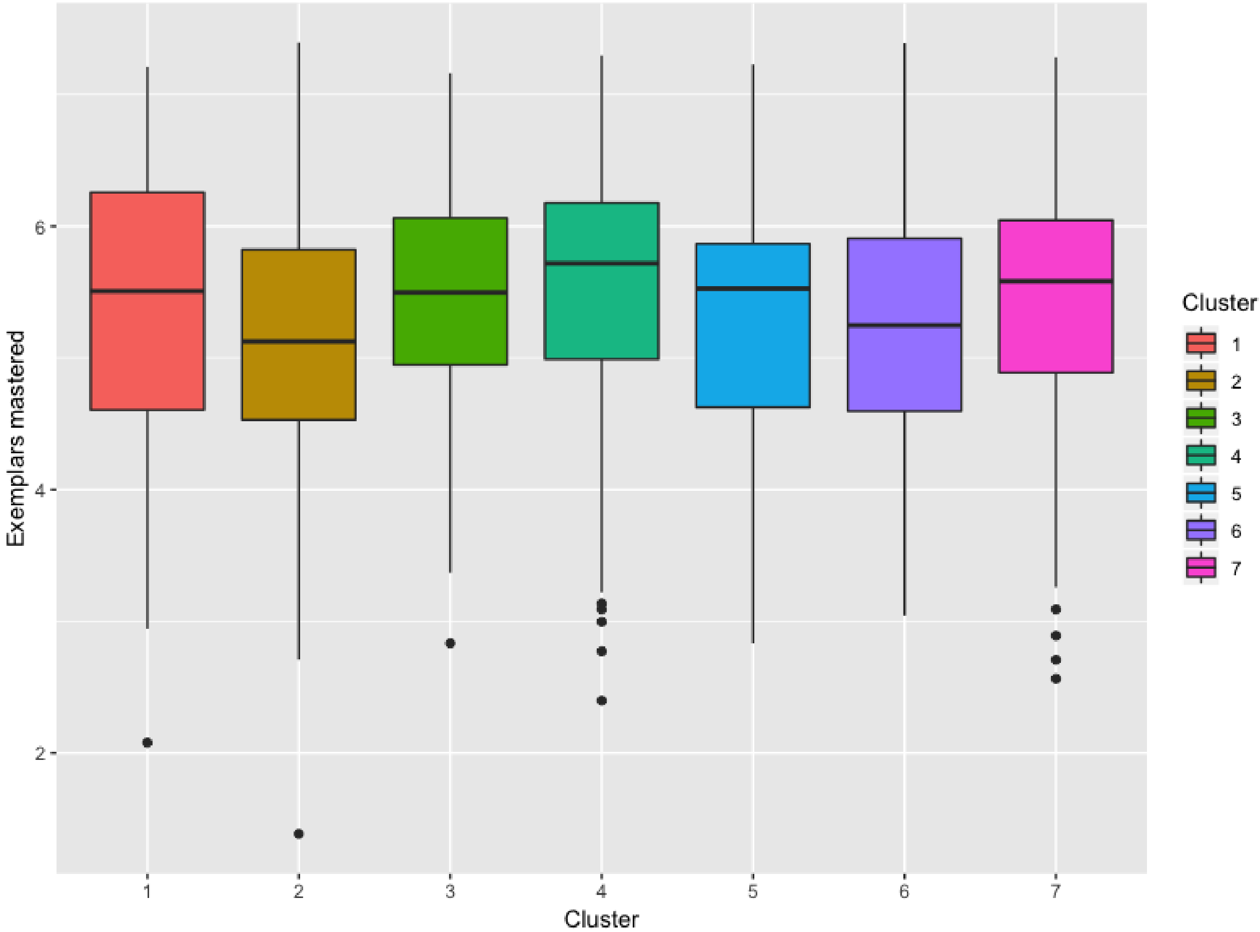


Table 2. Mean squared error comparison across clusters.

Cluster	Dominant challenging behavior	Mean squared error
1	Tantrums	0.30
2	Self-injurious behavior	0.34
3	Elopement	0.23
4	Stereotypy (low rate)	0.37
5	Noncompliance	0.30
6	Aggression	0.24
7	Stereotypy (high rate)	0.29

Box plots (Figure 5) for each of the 7 clusters depicts differences across clusters with respect to exemplar mastery and show the range of the exemplars mastered for each cluster, where the whiskers represent the minimum and maximum values (or 1.5 × the interquartile range, if outliers were present).

Figure 5. Box plots for each cluster. The box plots show the range of the exemplars mastered for each cluster, where the whiskers represent the minimum and maximum values. The line across each box is the median. The top of the box represents the third quartile. The bottom of the box represents the first quartile. Any points on the graph represent outliers in the clusters.



Increased treatment hours were associated with a significant increase in mastery (*P*<.001), and there were significant differences in mastery between clusters (*P*=.002); however, the interaction between treatment hours and cluster assignment was not significant (*P*=.28). Gender was nonsignificant (*P*=.051); however, the interaction between gender and cluster assignment did have a significant relationship with exemplar mastery (*P*=.018) (Table 3).

Table 3. Explanatory variables.

Variable	*P* value
Therapy hours	<.001
Gender	.051
Cluster	.002
Therapy hours × gender	.67
Therapy hours × cluster	.28
Gender and cluster	.02
Therapy hours, gender, and cluster	.63

Table 4 shows the averages for treatment hours and exemplars mastered for male, female, and combined clusters. Cluster 4 had the highest and Cluster 3 had the second-highest average number of exemplars mastered. Cluster 2 had the lowest average number of exemplars mastered.

Table 4. Average treatment hours and exemplars mastered across male, female, and combined gender clusters.

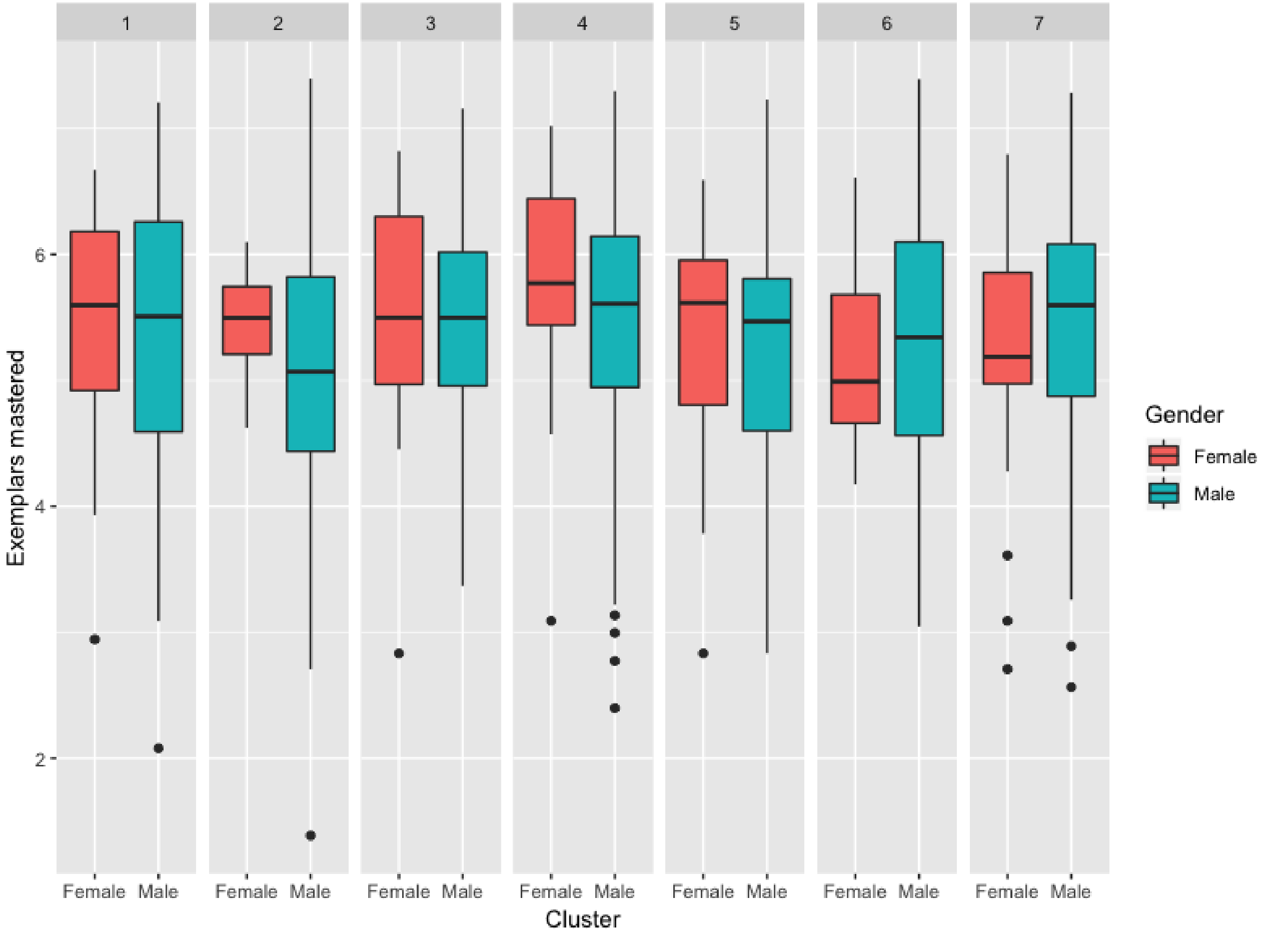
Cluster and dominant challenging behavior	Treatment hours	Exemplars mastered
Male		
Tantrums	6.61	5.33
Self-injurious behavior	6.64	5.05
Elopement	6.71	5.41
Stereotypy (low rate)	6.92	5.50
Noncompliance	6.47	5.26
Aggression	6.54	5.27
Stereotypy (high rate)	6.72	5.41
Female		
Tantrums	6.49	5.37
Self-injurious behavior	6.72	5.43
Elopement	6.66	5.50
Stereotypy (low rate)	6.90	5.80
Noncompliance	6.57	5.39
Aggression	6.58	5.15
Stereotypy (high rate)	6.66	5.13
Combined		
Tantrums	6.58	5.34
Self-injurious behavior	6.65	5.08
Elopement	6.70	5.43
Stereotypy (low rate)	6.91	5.55
Noncompliance	6.50	5.29
Aggression	6.55	5.24
Stereotypy (high rate)	6.71	5.38

Tukey Posthoc

Significant differences were found between Cluster 4 (low frequency stereotypy and moderate frequencies of other challenging behaviors) and Cluster 2 (self-injurious behavior) (P=.003) and between Cluster 4 and Cluster 6 (aggression) (P=.047). Overall, Cluster 4 had the highest rate of mastery while Cluster 2 had the lowest (Table 4); there was a significant difference between the clusters.

The interaction between gender and cluster assignment is depicted in Figure 6. Girls (P=.005) and boys (P=.03) in Cluster 4 mastered significantly more exemplars than the boys in Cluster 2. There was no significant difference between the girls in Cluster 2 and the girls and boys in Cluster 4. There were also no significant differences within clusters between genders (P=.003).

Figure 6. Box plots for each cluster and gender. The whiskers represent the minimum and maximum values. The line across each box is the median. The top of the box represents the third quartile. The bottom of the box represents the first quartile. Any points on the graph represent outliers in the clusters.



Discussion

The purpose of this study was to identify types of autism spectrum disorder based on engagement in 8 challenging behaviors (ie, aggression, disruption, elopement, noncompliance, obsessive behavior, self-injurious behavior, stereotypy, and tantrums) as well as examine group and gender differences in treatment response; *k*-means clustering analyses performed on male, female, and blended samples revealed 7 unique clusters. These findings differ from those of Stevens and colleagues [56], in which 8 male and female clusters were identified based on engagement in challenging behaviors. Similar to those found by Stevens and colleagues [56], the clusters in our study were found to have a single dominant challenging behavior. Only 2 of the measured challenging behaviors (ie, disruption and obsessive behaviors) did not appear as a dominant challenging behavior across the identified clusters. Furthermore, relatively low rates of disruption and obsessive behaviors were also observed across all the clusters. Cluster 1 had tantrums as its dominant challenging behavior, Cluster 2 had self-injurious behavior as its dominant challenging behavior, Cluster 3 had elopement as its dominant challenging behavior, Cluster 4 had stereotypy (low rate compared to cluster 7) as its dominant challenging behavior, Cluster 5 had noncompliance as its dominant challenging behavior, Cluster 6 had aggression as its dominant challenging behavior, and Cluster 7 had stereotypy (at a higher rate than Cluster 4) as its dominant challenging behavior. Neither obsessive behavior nor disruption appeared as a dominant behavior in any of the clusters.

To explore the relationship between skill mastery, treatment hours, cluster assignment, and gender, multiple linear regression was performed. Interactions between all the explanatory variables were also evaluated. In line with previous findings [30,31], the relationship between skill acquisition and treatment hours was found to be significant in our study ($P<.001$).

In addition to treatment hours, cluster assignment was found to be significantly related to skill mastery ($P=.002$). Results from the Tukey posthoc test revealed that Cluster 4, characterized by the dominant behavior stereotypy with moderate frequencies of other challenging behaviors, was found to have significantly stronger levels of skill mastery than both Cluster 2, characterized by self-injurious behavior, and Cluster 6, characterized by aggression ($P=.003$). These findings suggest that treatment response varies across individuals with autism spectrum disorder that engage in different topographies of challenging behaviors. In particular, participants who engaged in self-injurious behavior and aggression were found to have poorer response to treatment compared to those with low levels of stereotypy. It is likely that prioritizing the treatment of self-injurious behavior and aggression using appropriate behavior interventions based on the identified function of the behavior [63] will result in better long-term treatment outcomes for these individuals.

The only interaction between explanatory variables that was found to be significant in this study was cluster assignment and gender (P=.018). No significant gender differences were found, with respect to skill acquisition, within the same cluster. That is, boys and girls in the same cluster were found to have similar rates of skill acquisition (Table 4). Significant gender differences were found across clusters, however. Specifically, both girls and boys in Cluster 4 (stereotypy) displayed stronger rates of skill mastery than boys in Cluster 2 (self-injurious behavior); however, no significant differences were found between boys and girls in Cluster 4 and girls in Cluster 2. In previous research, gender was found to be a risk factor for the occurrence of challenging behaviors in individuals with autism spectrum disorder [8-12]. While the role of gender is unclear, this finding provides further support for the significant differences in treatment response across clusters, particularly for Cluster 4 and Cluster 2.

This study has several limitations that are important to consider. As a retrospective study, the analysis was limited to the existing data in the data set. Data on race and ethnicity were not available in the data set; therefore, representation across those demographics and any potential disparities in this sample are unknown. Furthermore, variables such as autism spectrum disorder symptom severity and IQ were not measured. Both symptom severity and IQ have been found to be related to engagement in challenging behaviors [2,3,7-9] as well as related to treatment response [27,35,36,38-45]. In particular, aggression and self-injurious behavior, the behaviors associated with slower skill acquisition in our study, have been linked to low IQ scores [8]. It would be worth exploring these variables in future research. In addition, the method used to aggregate the data for clustering results in a relatively small feature space of only 8 dimensions. These dimensions correspond to broad categories of challenging behaviors but do not capture other aspects related to those behaviors such as function. A future study could improve on this work by starting with a higher-dimension behavioral feature space, including functions of behavior, and then utilizing contemporary feature selection algorithms to derive the most meaningful subset of features to be fed to the unsupervised learning algorithm. In this case, use of a clustering algorithm that is more sophisticated may be warranted; the *k*-means algorithm takes a simple approach to clustering that relies upon regularly shaped clusters throughout the feature space. Finally, we note that additional studies to validate the clusters identified here would be valuable. In particular, the use of an additional cohort of participants which could be assigned to clusters and then have their assignments verified by clinicians using a broader set of medical records would be important to verify that the clusters identified here are generalizable beyond the study population.

This study is among the first to investigate types of autism spectrum disorder based on engagement in challenging behaviors and the impact of challenging behaviors on treatment response. Findings suggest that challenging behaviors do impact treatment response with specific topographies (ie, self-injurious behavior, aggression) being particularly detrimental. In future investigations, it would be worthwhile to map the function of the behavior (eg, attention, escape, tangible, automatic), in addition to the topography, and explore its impact on treatment response. Future research should also explore targeted interventions to improve skill acquisition based on cluster assignment, particularly for the clusters characterized by self-injurious behavior and aggression. Until such investigations are conducted, treatment providers should be aware that these behaviors seem to have a particularly negative impact on skill acquisition and interventions addressing these behaviors may be worth prioritizing in treatment. To further improve outcomes across individuals with autism spectrum disorder, attention must be given to segmentation within the disorder. Investigations, such as these, show the promise of unsupervised machine learning models in identifying types of autism spectrum disorder so that targeted treatments based on type membership may be explored. We recommend that clinicians who are interested in further exploring latent structural features of the autism spectrum, including challenging behaviors, proactively collect data to the greatest extent that is practical and unobtrusive. Such data, especially in aggregate, will be essential for gaining additional insights into autism spectrum disorder types with the ultimate goal of personalizing and optimizing treatment plans.

Acknowledgments

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Authors' Contributions

EL, ES, and DD conceived the research design. JGH, CPP, and EL conducted the analysis. ES, MN, and JGH performed the literature review. All authors contributed to drafting and revising the manuscript.

Conflicts of Interest

None declared.

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Original Paper

Physicians' Perspectives of Telemedicine During the COVID-19 Pandemic in China: Qualitative Survey Study

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Abstract

Background: Generalized restriction of movement due to the COVID-19 pandemic, together with unprecedented pressure on the health system, has disrupted routine care for non–COVID-19 patients. Telemedicine should be vigorously promoted to reduce the risk of infections and to offer medical assistance to restricted patients.

Objective: The purpose of this study was to understand physicians' attitudes toward and perspectives of telemedicine during and after the COVID-19 pandemic, in order to provide support for better implementation of telemedicine.

Methods: We surveyed all physicians (N=148), from October 17 to 25, 2020, who attended the clinical informatics PhD program at West China Medical School, Sichuan University, China. The physicians came from 57 hospitals in 16 provinces (ie, municipalities) across China, 54 of which are 3A-level hospitals, two are 3B-level hospitals, and one is a 2A-level hospital.

Results: Among 148 physicians, a survey response rate of 87.2% (129/148) was attained. The average age of the respondents was 35.6 (SD 3.9) years (range 23-48 years) and 67 out of 129 respondents (51.9%) were female. The respondents come from 37 clinical specialties in 55 hospitals located in 14 provinces (ie, municipalities) across Eastern, Central, and Western China. A total of 94.6% (122/129) of respondents' hospitals had adopted a telemedicine system; however, 34.1% (44/129) of the physicians had never used a telemedicine system and only 9.3% (12/129) used one frequently (≥1 time/week). A total of 91.5% (118/129) and 88.4% (114/129) of physicians were willing to use telemedicine during and after the COVID-19 pandemic, respectively. Physicians considered the inability to examine patients in person to be the biggest concern (101/129, 78.3%) and the biggest barrier (76/129, 58.9%) to implementing telemedicine.

Conclusions: Telemedicine is not yet universally available for all health care needs and has not been used frequently by physicians in this study. However, the willingness of physicians to use telemedicine was high. Telemedicine still has many problems to overcome.

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KEYWORDS

telemedicine; COVID-19; survey; physician

Introduction

The COVID-19 pandemic has drastically impacted global health care and dramatically changed the practice of health care [1,2]. Pervasive movement restriction and the unprecedented pressure on the health system has disrupted routine care for non–COVID-19 patients. Therefore, the COVID-19 pandemic has rapidly and fundamentally altered the pattern medical practitioners follow to provide care to patients. To better mitigate and manage the spread of COVID-19, hospitals can replace some routine medical services with telemedicine to improve the efficiency of their health care system [3].

Since telemedicine was first introduced in the late 1950s, it has been used in all aspects of health care with the widespread use of telecommunication technology [4]. In a bibliometric analysis of health technology and informatics, telemedicine was identified as one of the three most common keywords [5]. Now the application of telemedicine has expanded from providing health care services in hospitals, outpatient departments, and specialist offices, as well as between health care providers, to deliver care in patients' homes [6]. One study has shown that achieving instant patient access, overcoming service gaps, and improving quality are important motivators for physicians to implement telemedicine in acute care units, while issues such as licensure, credentialing, malpractice protection, cost, and reimbursement are barriers to successful implementation [7]. Another study identified that the main challenges in establishing telemedicine systems in developing countries are the high cost of telemedicine systems and solutions, slow clinical acceptance of telemedicine and resistance to change, and lack of the required information and telecommunications technology infrastructure for telemedicine. The major recommendations include setting clear goals for the project, selecting the appropriate application of medical areas and priorities, and adopting user-friendly interfaces [8].

Our study focused on the context of COVID-19 to investigate the current usage of telemedicine during the pandemic in China. With the development of telemedicine, the evaluation of telemedicine is particularly important [9]. The selection of statistical methods is a key step in telemedicine evaluation. The following statistical methods have been used extensively in telemedicine evaluation: statistical comparison, agreement evaluation (κ statistic), and the receiver operating characteristic curve [10-14]. Since telemedicine evaluation needs to explore various outcomes, it may be appropriate to evaluate from a multidisciplinary perspective and use various statistical methods [10]. However, there is a lack of empirical research about telemedicine in different specialties [15]. Some researchers have provided theoretical and practical evidence on the significance of using telemedicine and virtual care to treat patients remotely during the COVID-19 pandemic [16]. Major health organizations around the world, including the World Health Organization, the US Centers for Disease Control and Prevention, and the American Medical Association, have advocated for the use of telemedicine during the COVID-19 pandemic and have taken steps to promote its use [17-19]. During the COVID-19 pandemic, telemedicine has been considered a useful tool to relieve pressure on overburdened health systems. Physicians' willingness or unwillingness to use telemedicine is a well-known factor in facilitating or inhibiting telemedicine acceptance [20]. In addition, some studies noted that the adoption of telemedicine systems depends on physicians' and patients' satisfaction with the use of the telemedicine service [21]. However, physicians' perspectives on telemedicine visits have not been fully investigated.

To promote the usage of telemedicine during the COVID-19 pandemic, the current state of telemedicine and physicians' perspectives need to be explored. To better understand the development of telemedicine during the COVID-19 pandemic and to summarize the problems of telemedicine in response to the pandemic, we collected the opinions and suggestions of 148 young and middle-aged physicians regarding the application of telemedicine during the COVID-19 pandemic. These recommendations provide valuable insights for developing and improving telemedicine in the later stages of the COVID-19 pandemic and play an important role in guiding the development of telemedicine.

Methods

Participants

We surveyed all physicians (N=148), from October 17 to 25, 2020, who attended the clinical informatics PhD program at West China Medical School, Sichuan University, China. These physicians passed the program's application and examination process and the hospital academic committee's review. They had high levels of informatics literacy and a certain understanding of information technology and telemedicine at their hospitals. The physicians came from 57 hospitals in 16 provinces (ie, municipalities) across China, 54 of which are 3A-level hospitals, two are 3B-level hospitals, and one is a 2A-level hospital. The Ministry of Health in China categorizes Chinese hospitals into three levels—primary, secondary, and tertiary hospitals—based on the quality of the health care provided, medical education, and research. Each level is further subdivided into three subsidiary levels: A, B, and C. In 2019, there were 1246 hospitals at the 3A level [22], the highest level of hospitals in China.

This study was approved by the Institutional Review Board at West China Medical School, Sichuan University (IRB17-75).

Procedure

We conducted a survey using semistructured and open-ended questions to understand physicians' perspectives of telemedicine during the COVID-19 pandemic in China. Prior to completing the survey, the physicians spent more than 3 hours on coursework related to telemedicine. The questionnaire was derived from the literature on telemedicine satisfaction and experts in telemedicine [23-28]. We conducted a pilot test within our research group. The questionnaire consisted of three sections (Multimedia Appendix 1). The first part included demographic and clinical characteristics (age, gender, clinical specialty, etc). The second part consisted of statements that were rated on a 7-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). Statements were identified from previous literature that related to physicians' perspectives on and attitudes toward telemedicine, such as overall satisfaction, behavioral intention, increasing the burden, safety issues regarding patient data, and hindering communication with patients, among others. In addition, we collected information about the current usage of telemedicine in their hospitals. The final section consisted of open-ended questions that included physician attitudes, concerns, and suggestions about telemedicine and any other comments related to telemedicine. The questionnaire was administered in a face-to-face manner.

Data Gathering and Analysis

After completing the questionnaire, the data were tabulated and analyzed. All the physicians' responses to the open-ended questions were entered into Microsoft Office Excel 2007 and were subjected to qualitative content analysis by reviewers. The analytical process was conducted by first cleaning the text, followed by extracting themes, and then developing categories. Free-text answers were summarized and assessed independently by two reviewers using a standardized evaluation process. A third reviewer reviewed by adjudication in cases of disagreement. The research team members repeatedly and independently read the answer summaries and validated the accuracy and meaning of the contents. Lastly, the results of the study were confirmed by all researchers in the team. The responses to the Likert scale–based statements were analyzed quantitatively by expressing them as whole numbers. The percentage of respondents who were in agreement with a statement was obtained by dividing the sum of the *strongly agree*, *agree*, and *somewhat agree* responses by the total number of responses to that statement. For questions using a 7-point Likert scale and questions that collected numerical demographic information, we reported mean values with standard deviations. For each clinical specialty, we calculated *P* values to determine the statistical significance of the differences between the scores of usability and willingness. Two-sided *P* values of .01 or less were deemed to meet statistical significance.

Results

Physician Demographics and Characteristics

We received 129 completed survey forms—direct survey handout and return on the day—with a response rate of 87.2% (129/148). Out of 129 respondents, 67 (51.9%) were females and 62 (48.1%) were males. The average age of the respondents was 35.6 (SD 3.9) years (range 23-48 years). The respondents came from 37 clinical specialties in 55 hospitals in China. These hospitals were located in 14 provinces (ie, municipalities) across China, including the three main provincial regions: Western China (n=5), Central China (n=4), and Eastern China (n=5). Among these 55 hospitals, 52 were 3A-level hospitals (ie, the highest level of hospital in China), two were 3B-level hospitals, and one was a 2A-level hospital. Table 1 shows the demographic characteristics of the respondents.

All hospitals in China are divided into three grades, each with three sublevels (ie, A, B, and C), with the highest grade being 3A. In principle, hospitals rated as a 3A-level hospital must meet very high standards in terms of beds, doctors, equipment, and quality of service.

Table 1. Demographic and clinical practice characteristics.

Participant demographics	Value (N=129)
Age (years)	
Mean (SD)	35.6 (3.9)
Range, n (%)	
23-29	4 (3.1)
30-39	105 (81.4)
40-48	20 (15.5)
Sex, n (%)	
Female	67 (51.9)
Male	62 (48.1)
Title, n (%)	
Resident	6 (4.7)
Senior physician	89 (69.0)
Specialist	34 (26.4)
Experience on the job (years)	
Mean (SD)	9.5 (4.5)
Range, n (%)	
1-5	27 (20.9)
6-10	57 (44.2)
11-20	42 (32.6)
21-25	3 (2.3)
Electronic health record use (years)	
Mean (SD)	8.0 (2.8)
Range, n (%)	
0-5	25 (19.3)
6-10	82 (63.6)
11-16	22 (17.1)
Provinces where hospitals were located per region (n=14), n (%)	
Western China[a]	5 (35.7)
Central China[b]	4 (28.6)
Eastern China[c]	5 (35.7)
Hospital level, n (%)	
3A	52 (94.6)
2A	2 (3.6)
3B	1 (1.8)

[a]This includes Sichuan, Chongqing, Guangxi, Xinjiang, and Yunnan.

[b]This includes Shanxi, Henan, Hunan, and Jiangxi.

[c]This includes Beijing, Fujian, Guangdong, Shandong, and Liaoning.

Current Use of Telemedicine

Among the 129 respondents, 94.6% (122/129) of the respondents' hospitals adopted a telemedicine system. Only 5.4% (7/129) of the respondents did not know whether telemedicine was used in the hospital. A total of 34.1% (44/129) of physicians had never used a telemedicine system, 45.0% (58/129) used one occasionally (≤1 time/month), 11.6% (15/129) used one often (>1 time/month – <1 time/week), and only 9.3% (12/129) used one frequently (≥1 time/week). Depending on the question asked, 52% (44/85) of respondents were satisfied (responses of *strongly satisfied* plus *satisfied* and *somewhat satisfied*) with the telemedicine system (mean 4.7, SD 0.82).

Only 57 out of 129 (44.2%) physicians had participated in telemedicine training. A total of 32% (18/57) of those respondents were satisfied with their training (mean 4.2, SD 0.64). Among physicians who had used telemedicine systems, 11% (9/85) of them believed that electronic medical records were integrated into telemedicine. A total of 32% (27/85) of physicians believed that telemedicine had a decision support system (Table 2).

Table 2. Current use of telemedicine system.

Question or statement	Value (N=129)
Has your hospital adopted a telemedicine system? (yes), n (%)	122 (94.6)
How often do you use the telemedicine system?, n (%)	
Not at all	44 (34.1)
≤1 time/month	58 (45.0)
>1 time/month – <1 time/week	15 (11.6)
≥1 time/week	12 (9.3)
What is your overall satisfaction with the telemedicine system?[a] (n=85)	
Satisfied, n (%)	44 (51.8)
Score, mean (SD)	4.7 (0.82)
Score, range	3-7
Have you taken telemedicine training? (yes), n (%)	57 (44.2)
What is your overall satisfaction with the telemedicine training?[a] (n=57)	
Satisfied, n (%)	18 (31.6)
Score, mean (SD)	4.2 (0.64)
Score, range	2-5
Does the telemedicine system integrate electronic medical records?[b]	
Yes, n (%)	9 (7.0)
Score, mean (SD)	4.2 (0.42)
Score, range	4-5
Does the telemedicine system integrate clinical decision support?[b]	
Yes, n (%)	27 (20.9)
Score, mean (SD)	4.3 (0.67)
Score, range	3-5

[a]Satisfaction scores range from 1 (strongly dissatisfied) to 7 (strongly satisfied).

[b]Agreement scores range from 1 (strongly disagree) to 7 (strongly agree).

Telemedicine During COVID-19

Of the 129 respondents, 60.5% (78/129) indicated that their specialty was suitable (responses of *strongly suitable* plus *suitable* and *somewhat suitable*) for adopting telemedicine during the COVID-19 pandemic (mean 5.0, SD 1.28). A total of 91.5% (118/129) of respondents would be willing to adopt telemedicine during the COVID-19 pandemic (mean 5.7, SD 1.02). In the group with telemedicine-appropriate specialties, obstetrics and gynecology had the highest mean value (mean 6.3, SD 0.97) and dermatology had the lowest mean value (mean 4.2, SD 0.75). Regarding willingness to adopt telemedicine, radiologists had the highest mean value (mean 6.4, SD 0.80) and ophthalmologists had the lowest mean value (mean 4.6, SD 0.49). For each specialty, we calculated *P* values to determine the statistical significance of the differences between the scores of usability and willingness (*P*>.01). The detailed attitudes and opinions about telemedicine on the part of the physicians are shown in Table 3.

Table 3. Physicians' attitudes and opinions on the use of telemedicine in different subspecialties.

Specialty	Is telemedicine suitable for your specialty during the COVID-19 pandemic?[a]			Are you willing to use a telemedicine system during the COVID-19 pandemic?[b]			*P* value
	Score, range	Score, mean (SD)	Suitable (yes), n (%)	Score, range	Score, mean (SD)	Willing (yes), n (%)	
All (N=129)	2-7	5.0 (1.28)	78 (60.5)	3-7	5.7 (1.02)	118 (91.5)	N/A[c]
Dermatology (n=5)	3-5	4.2 (0.75)	—[d]	5-7	6.2 (0.98)	—	.012
Urology (n=6)	2-6	4.2 (1.21)	—	5-7	5.8 (0.90)	—	.03
Laboratory (n=5)	3-7	4.2 (1.47)	—	4-7	6.0 (1.27)	—	.10
Neurosurgery (n=6)	3-7	4.3 (1.25)	—	4-7	5.3 (0.94)	—	.18
Nephrology (n=5)	4-5	4.4 (0.49)	—	5-7	6.0 (0.89)	—	.013
General surgery (n=9)	2-7	4.6 (1.34)	—	4-7	5.4 (1.07)	—	.16
Ophthalmology (n=5)	4-7	4.8 (0.75)	—	4-5	4.6 (0.49)	—	.67
Pediatrics (n=9)	4-6	5.0 (0.67)	—	4-7	5.9 (1.10)	—	.07
Anesthesiology (n=12)	2-7	5.1 (1.38)	—	5-7	6.0 (0.91)	—	.08
Oncology (n=8)	4-7	5.3 (1.09)	—	5-7	5.6 (0.86)	—	.49
Respiratory (n=6)	4-7	5.3 (0.94)	—	4-7	5.8 (1.07)	—	.45
Cardiothoracic surgery (n=7)	4-7	5.5 (1.28)	—	5-7	6.1 (0.83)	—	.50
Orthopedics (n=8)	3-7	5.8 (1.30)	—	5-7	6.0 (1.00)	—	.69
Radiology (n=5)	5-7	6.0 (0.89)	—	5-7	6.4 (0.80)	—	.52
Obstetrics and gynecology (n=8)	4-7	6.3 (0.97)	—	4-7	5.9 (1.05)	—	.50

[a]This includes *strongly suitable* plus *somewhat suitable* and *suitable*. Suitability scores range from 1 (strongly unsuitable) to 7 (strongly suitable).
[b]This includes *strongly willing* plus *willing* and *somewhat willing*. Willingness scores range from 1 (strongly unwilling) to 7 (strongly willing).
[c]N/A: not applicable; *P* values were only calculated for individual specialties.
[d]The number of respondents who found telemedicine to be suitable and were willing to use it was not reported for individual specialties.

Main Concerns of Adopting Telemedicine

Based on the findings of the survey, the major concerns regarding the use of telemedicine included the following: the inability to complete an in-person physical examination (101/129, 78.3%), the inability to communicate well with patients (32/129, 24.8%), the instability of the telemedicine system (30/129, 23.3%), and no assurance of patient medical safety (23/129, 17.8%) (Table 4).

Table 4. Major concerns regarding the use of telemedicine.

Major concerns	Respondents (N=129), n (%)
Cannot communicate well with patients	32 (24.8)
No assurance of patient medical safety	23 (17.8)
Inability to do an in-person physical examination	101 (78.3)
Unstable telemedicine system	30 (23.3)

Barriers to the Use of Telemedicine

Overall, 58.9% (76/129) of respondents agreed that a physician's inability to examine patients will hinder clinical decision making. A total of 44.2% (57/129) of respondents agreed that telemedicine makes it easier for patients' data to be stolen, compromised, or hacked. Approximately one-quarter of the respondents (32/129, 24.8%) agreed that the lack of person-to-person contact in telemedicine can damage the doctor-patient relationship and trust. Only 15.5% (20/129) of respondents agreed that during the COVID-19 pandemic, the use of telemedicine will increase the burden on physicians (Table 5).

Table 5. Barriers to adopting telemedicine.

Barrier	Score, range	Score, mean (SD)	Respondents who agree[a] (N=129), n (%)	Respondents who disagree[a] (N=129), n (%)
The lack of person-to-person contact in telemedicine can damage the doctor-patient relationship and trust.	1-7	3.6 (1.89)	32 (24.8)	62 (48.1)
A physician's inability to examine patients will hinder clinical decision making.	1-7	4.5 (1.02)	76 (58.9)	23 (17.8)
During the COVID-19 pandemic, the use of telemedicine will increase the burden on physicians.	1-6	3.0 (1.20)	20 (15.5)	87 (67.4)
Telemedicine makes it easier for patient data to be stolen, compromised, or hacked.	1-7	4.1 (1.23)	57 (44.2)	42 (32.6)

[a]Agreement includes *strongly agree* plus *somewhat agree* and *agree*. Disagreement includes *strongly disagree* plus *somewhat disagree* and *disagree.* Scores range from 1 (strongly disagree) to 7 (strongly agree).

Physicians' Comments

In the open-ended section of the questionnaire, a total of 127 respondents out of 129 (98.4%) made comments regarding the obstacles to adopting telemedicine and made suggestions for improving telemedicine (Tables 6 and 7). Two respondents did not make comments or suggestions about telemedicine.

The main barriers to implementation cited by physicians included the inability to examine patients personally (48/127, 37.8%), insufficient infrastructure support for telemedicine (40/127, 31.5%), issues concerning the quality of patients' data (28/127, 22.1%), communication issues with patients (18/127, 14.2%), network issues (13/127, 10.2%), and lack of policy support (10/127, 7.9%). Table 6 lists the physicians' comments regarding obstacles to the use of telemedicine.

Physicians believed that telemedicine could be promoted through the following incentives: performance measures (60/127, 47.2%), increased telemedicine equipment (22/127, 17.3%), policy support (21/127, 16.5%), financial support (19/127, 15.0%), technical support (18/127, 14.2%), increased training (18/127, 14.2%), and increased telemedicine publicity (14/127, 11.0%) (Table 7).

Table 6. Physicians' comments regarding obstacles to the use of telemedicine.

Main obstacles to adoption of telemedicine[a]	Respondents (n=127), n (%)
Inability to examine patients personally	48 (37.8)
Insufficient infrastructure support for telemedicine	40 (31.5)
Issues concerning the quality of patients' data	28 (22.1)
Communicating issues with patients	18 (14.2)
Network issues	13 (10.2)
Lack of policy support	10 (7.9)
Others[b]	49 (38.6)

[a]There were a total of 206 comments.

[b]Other comments included low patient acceptance (n=5), lack of funds (n=4), lack of performance measures (n=4), inadequate telemedicine promotion (n=3), etc.

Table 7. Physicians' comments regarding promoting telemedicine.

Suggestions for promoting telemedicine[a]	Respondents (n=127), n (%)
Performance measures[b]	60 (47.2)
Increase telemedicine equipment	22 (17.3)
Policy support	21 (16.5)
Financial support	19 (15.0)
Technical support	18 (14.2)
Increase training	18 (14.2)
Increase telemedicine publicity	14 (11.0)
Others[c]	73 (57.5)

[a]There were a total of 242 comments.

[b]Performance measures included monetary incentives and professional incentives (eg, continuing education credits, facilitating physician promotions, and/or offering time-saving measures for physicians in other aspects of the workday).

[c]Other comments included developing guidelines for telemedicine (n=8), optimization of telemedicine systems (n=7), solving network issues (unable to connect, slow internet performance, etc) (n=5), including telemedicine coverage in health insurance (n=4), increasing the convenience of telemedicine (n=4), harmonious doctor-patient relationships (n=4), etc.

Main Reasons for Being Willing or Unwilling to Use Telemedicine

Physicians' attitudes toward telemedicine were positive, with 88.4% (114/129) of respondents stating that they were willing to adopt telemedicine. Only 8.5% (11/129) of respondents were unwilling to adopt telemedicine, and 4 respondents out of 129 (3.1%) were undecided about whether or not they were willing to adopt telemedicine. The main reasons physicians were willing to adopt telemedicine included convenience for patients (56/114, 49.1%), optimization of medical resources (31/114, 27.2%), and improving the level of medical care (16/114, 14.0%). The main reasons for being willing or unwilling to use telemedicine are given in Table 8.

Table 8. Physicians' attitudes toward telemedicine.

Main reasons physicians were willing or unwilling to use telemedicine[a]	Respondents (N=129), n (%)
Willing (n=114)	114 (88.4)
Convenient for patients	56 (49.1)
Optimized medical resources	31 (27.2)
Improved level of medical care	16 (14.0)
The trend of medical development	8 (7.0)
The COVID-19 pandemic	6 (5.3)
Others[b]	25 (21.9)
Unwilling (n=11)	11 (8.5)
The physician's inability to personally examine a patient will hinder clinical decision making	6 (54.5)
More time spent	3 (27.3)
Low medical fees	2 (18.2)
Concerns about the quality of care	2 (18.2)
Cannot provide valid patient information	2 (18.2)
Others[c]	6 (54.5)
Undecided	4 (3.1)

[a]There were a total of 163 reasons.

[b]Other reasons for being willing to use telemedicine included increased diagnosis and treatment efficiency (n=5), reduced patient burden (n=4), conducive to medical equity (n=2), reduced medical costs (n=1), enhanced patient satisfaction (n=1), etc.

[c]Other reasons for being unwilling to use telemedicine included low economic gain (n=1), patients' distrust of telemedicine (n=1), medical malpractice (n=1), etc.

Discussion

Principal Findings

Although telemedicine has been used in various clinical specialties for decades [29], the emergence of the COVID-19 pandemic has highlighted the importance of telemedicine [30]. In the midst of the global COVID-19 catastrophe, a focus on telemedicine could play a critical role in the provision of global health care and may become a necessity for the general population [31]. In order to make the best use of telemedicine, we need to gain insight into physicians' perceptions of telemedicine.

This study showed that the surveyed physicians had a high willingness to use telemedicine. The reasons for their high willingness were manifold but included the COVID-19 pandemic, telemedicine training courses, as well as young physicians in academic centers. The COVID-19 pandemic forced physicians to quickly adapt and use telemedicine [32]. Physicians' willingness to adopt telemedicine may also be related to the COVID-19 pandemic's movement-restriction policy [33]. Before answering the questionnaire, all the physicians spent more than 3 hours on coursework related to telemedicine. The telemedicine training course increased physicians' awareness of, knowledge about, and attitudes toward telemedicine. There are studies that indicate that the knowledge and perception of health care professionals affect telemedicine adoption [34,35]. Moreover, younger physicians have a greater openness and willingness to adopt telemedicine [36]. One's willingness to use telemedicine may also be influenced by one's attitude toward telemedicine itself, one's level of technology anxiety, and the patient-physician relationship [37]. These factors that were associated with a high willingness to use telemedicine were identified and must be considered in the long-term development of telemedicine.

Although telemedicine has found its way to nearly all clinical specialties, its use is uneven across specialties [38,39]. To promote the development of telemedicine in different specialties, we analyzed the willingness to use, and perceptions of, telemedicine on the part of physicians in different specialties. Due to the uneven distribution of the number of specialists, only specialties that included more than 5 participating physicians were analyzed. Although physicians' willingness to participate in telemedicine was different from the usability of telemedicine in each specialty, there was no correlation between them.

The most obvious concerns and obstacles to telemedicine are limited in-person physical exams and the lack of vital sign assessment. The inability to complete an in-person physical examination was the highest concern for physicians (101/129, 78.3%) and was the main reason physicians cited it as a barrier to implementing telemedicine. This result is consistent with research from the United States [40]. This was mainly due to the concern by physicians that not being able to examine patients in person would affect clinical diagnosis. Whether in the learning stage or late in their careers, physicians want to carefully examine each patient personally. In telemedicine, the inability to examine the patient in person not only affects the physicians' habits, but also sound and light present during telemedicine examinations can affect physicians' diagnoses and treatment recommendations [41]. A well-lit environment and diffuse lighting to reduce glare allow physicians to detect physical examination findings more clearly, such as tremors, convulsions, and subtle facial expressions. Poor sound quality may limit understanding and mutual contact [41-44]. Therefore, health care professionals must be reassured that telemedicine is not a threat to their clinical decision making and that it could allow them to focus on patients who urgently need help. Some authors suggested that telemedicine might be best used in conjunction with face-to-face visits. Physicians can rely on proxies for examination [45].

An important aspect in the application of telemedicine will be the integration of telemedicine with the current health system workflows and the connection to the electronic health record [46]. In order to maximize the benefits of utilizing telemedicine technology, technologies including remote patient monitoring equipment need to be automatically synchronized to the patient's chart, so that physicians can instantly obtain patient data [47]. Clinical decision support in telemedicine should also be enhanced to reduce medical errors.

This study suggests that there are many challenges and risks to telemedicine that need to be addressed before the technology is widely endorsed by physicians. These challenges may be due to regulation, incentives involving telemedicine, effective telemedicine training, malpractice insurance coverage for telemedicine, security and confidentiality of patient data, and telemedicine technology. These are in line with the findings of the other studies [48]. Physicians are less likely to use telemedicine if they are not adequately compensated for their time and effort [49]. Therefore, addressing the barriers to the development of telemedicine will require collaboration and efforts by health care institutions, policy makers, hospital administrators, physicians, and patients.

Limitations of the Study

This study has potential limitations. First, this is a survey-based study and is subject to respondent bias inherent in all survey-based studies. Second, the survey was only about Chinese physicians. Incentive effects may differ in other countries due to cultural differences. Another limitation is the limited sample size and the descriptive nature of the study, which may not be able to reflect the opinions of all physicians in each hospital. However, considering the limited use of telemedicine in China and the lack of knowledge about telemedicine among general physicians, it is difficult to collect opinions through large random sampling. We recruited participants who were physicians and enrolled in a PhD program in clinical informatics. Most of them were also involved with the hospital management team. Therefore, in contrast to general physicians, they have a basic understanding of clinical informatics as well as medical information systems in their own hospital. In addition, the overall response rate was very high (87.2%) and included a variety of clinical specialties. The relatively younger physicians (23 to 48 years old) from the highest-level hospitals represented those who might be more familiar with telemedicine and digital technology. The responses were collected from 55 hospitals in Eastern, Central, and

Western China, as it was a study representing various clinical subspecialties. Moreover, participants spent more than 3 hours on coursework related to telemedicine before completing the survey, so that they had a comprehensive understanding of telemedicine. The survey questions we asked were inherently pragmatic, and the responses to these questions faithfully reflected the physicians' sentiments.

Conclusions

The results of this survey indicate that, although telemedicine cannot yet be used universally for all health care needs and cannot fully replace in-person physical examinations, physicians' willingness to use telemedicine was high. The modality of telemedicine is a tool worthy of careful evaluation and consideration by clinical subspecialties and their medical systems.

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Authors' Contributions

JL and SL conceived the study. JL, SL, TZ, and YB performed the analysis, interpreted the results, and drafted the manuscript. All authors revised the manuscript. All authors read and approved the final manuscript.

Conflicts of Interest

None declared.

Multimedia Appendix 1
Telemedicine questionnaire.
[PDF File (Adobe PDF File), 76 KB - medinform_v9i6e26463_app1.pdf]

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Original Paper

Physicians' Attitudes Toward Telemedicine Consultations During the COVID-19 Pandemic: Cross-sectional Study

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Abstract

Background: To mitigate the effect of the COVID-19 pandemic, health care systems worldwide have implemented telemedicine technologies to respond to the growing need for health care services during these unprecedented times. In the United Arab Emirates, video and audio consultations have been implemented to deliver health services during the pandemic.

Objective: This study aimed to evaluate whether differences exist in physicians' attitudes and perceptions of video and audio consultations when delivering telemedicine services during the COVID-19 pandemic.

Methods: This survey was conducted on a cohort of 880 physicians from outpatient facilities in Abu Dhabi, which delivered telemedicine services during the COVID-19 pandemic between November and December 2020. In total, 623 physicians responded (response rate=70.8%). The survey included a 5-point Likert scale to measure physician's attitudes and perceptions of video and audio consultations with reference to the quality of the clinical consultation and the professional productivity. Descriptive statistics were used to describe physicians' sociodemographic characteristics (age, sex, designation, clinical specialty, duration of practice, and previous experience with telemedicine) and telemedicine modality (video vs audio consultations). Regression models were used to assess the association between telemedicine modality and physicians' characteristics with the perceived outcomes of the web-based consultation.

Results: Compared to audio consultations, video consultations were significantly associated with physicians' confidence toward managing acute consultations (odds ratio [OR] 1.62, 95% CI 1.2-2.21; *P*=.002) and an increased ability to provide patient education during the web-based consultation (OR 2.21, 95% CI 1.04-4.33; *P*=.04). There was no significant difference in physicians' confidence toward managing long-term and follow-up consultations through video or audio consultations (OR 1.35, 95% CI 0.88-2.08; *P*=.17). Video consultations were less likely to be associated with a reduced overall consultation time (OR 0.69, 95% CI 0.51-0.93; *P*=.02) and reduced time for patient note-taking compared to face-to-face visits (OR 0.48, 95% CI 0.36-0.65; *P*<.001). Previous experience with telemedicine was significantly associated with a lower perceived risk of misdiagnosis (OR 0.46, 95% CI 0.3-0.71; *P*<.001) and an enhanced physician-patient rapport (OR 2.49, 95% CI 1.26-4.9; *P*=.008).

Conclusions: These results indicate that video consultations should be adopted frequently in the new remote clinical consultations. Previous experience with telemedicine was associated with a 2-fold confidence in treating acute conditions, less than a half of the perceived risk of misdiagnosis, and an increased ability to provide patients with health education and enhance the physician-patient rapport. Additionally, these results show that audio consultations are equivalent to video consultations in providing remote follow-up care to patients with chronic conditions. These findings may be beneficial to policymakers of e-health programs in low- and middle-income countries, where audio consultations may significantly increase access to geographically remote health services.

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KEYWORDS

audio consultation; clinical decision-making; clinical training; communication; COVID-19; outpatient department; perception; telemedicine; United Arab Emirates; video consultation

Introduction

The COVID-19 pandemic has caused an enormous burden on the health care system and health care delivery worldwide [1-4]. As social distancing and quarantining became the new normal, face-to-face clinical visits plummeted, causing the health care system to rapidly shift to telemedicine to leverage their response to the pandemic [5-8]. Telemedicine created new opportunities for patient care in the context of the COVID-19 pandemic and thus reduced health care disparities [9,10]. Telemedicine is available in various modalities including patient portals, emails, text messages, telemonitoring, store-and-forward, audio consultations, and real-time video consultations [10-13]. The wide variety in communication channels offer different opportunities for providers to manage patients who are in quarantine or live in remote areas, which reduces the risk of disease transmission and improves access to health care services [5,9,14,15].

Owing to the growing concern regarding the risk of workplace transmission, the use of telemedicine services increased globally [16-19], and the United Arab Emirates is no different. In March 2020, Abu Dhabi launched its first Telemedicine Virtual Outpatient Clinic to support the continuity of patient care [20]. It has been estimated that within only 1 month, physicians across Abu Dhabi SEHA hospitals performed over 28,000 virtual consultations [21,22].

Studies conducted on telemedicine during the COVID-19 pandemic, while yielding meaningful insights on its role, have largely been based on physician knowledge of telemedicine in specific subspecialities and have been limited to descriptive data of certain encounters rather than quantifying their association. Currently, the effect of video vs audio consultations on physicians' attitude toward telemedicine is unclear [23,24]. Moreover, barriers against its full implementation beyond the context of the COVID-19 pandemic remain unexplored. Identifying these barriers within each modality, which prevent their successful adoption by health care providers, is essential for directing future infrastructure to modernize the health care system and improve telemedicine utilization and outcomes. This study aimed to describe physicians' attitudes toward the use of telemedicine services in Abu Dhabi during the COVID-19 pandemic. We also aimed to explore the effects of audio vs video consultations and physicians' sociodemographic characteristics on their confidence during the clinical consultation, perceived quality of care, and perceived effects of professional productivity. Future studies are needed to objectively assess the effect of telemedicine modalities on the quality of care and professional productivity and to guide future infrastructure investments to assure embracing this new opportunity to provide high-quality health care to a larger number of patients in the post–COVID-19 era.

Methods

Study Design and Ethics Approval

This was a survey-based study conducted on physicians in outpatient facilities in Abu Dhabi, which provided telemedicine services during the COVID-19 pandemic between November and December 2020. Ethics approval was obtained from the institutional review board of Khalifa University (protocol# H21-006-2020) and of the Abu Dhabi COVID-19 Research Committee of the Department of Health in Abu Dhabi (reference# DOH/CVDC/2020/1747). Surveys were administered through the Department of Health and SEHA, these being the major health authorities in Abu Dhabi. The institutional review board or ethics committee at each participating institution approved the study protocol and survey. Electronic written consent was waived for this data-only study owing to the deidentified nature of this survey. The present study followed the STROBE (Strengthening the Reporting of Observational Studies in Epidemiology) reporting guidelines for cross-sectional studies [25].

Subject Selection and the Inclusion and Exclusion Criteria

The survey was administered to a cohort of 880 physicians at outpatient facilities in Abu Dhabi, who met the following inclusion criteria: being a physician practicing at an outpatient facility in Abu Dhabi and providing audio or video consultations during the COVID-19 pandemic from January to November 2020. Exclusion criteria were being of another allied health care profession such as nurses, pharmacists, and technicians (as our study targeted physicians only) or physicians who did not work at outpatient departments and who did not use telemedicine during the COVID-19 pandemic. From a total of 880 physicians listed, 623 responded to the survey (response rate=70.8%).

Survey Development, Piloting, and Data Collection

A web-based structured survey containing multiple-choice questions was developed by reviewing published telemedicine surveys and their instruments [26-28]. The web-based survey had 6 components, which contained a total of 42 questions related to physicians' perceptions and attitudes toward telemedicine. A pilot survey was conducted, which included a cohort of 25 physicians in Abu Dhabi, who frequently used telemedicine during the COVID-19 pandemic. The main web-based survey was developed using the Microsoft Forms platform (Microsoft Corp) and was sent to the physicians at outpatient facilities via the hospital's internal email system. To reduce the risk of attrition bias, we ensured generating a good rapport between on-site principal investigators and the study participants by sending customized invitations [29,30]. Furthermore, a follow-up email was sent 1 week apart from the initial date of survey distribution to remind nonresponders to participate in the survey.

Study Variables and Outcomes

This was a self-administered survey that gathered data on physicians' sociodemographic characteristics including age, sex, telemedicine modality, clinical specialty, designation, number of years in practice, and past experience with telemedicine. We also gathered data using a 5-point Likert scale to assess (1) physicians' current experience with telemedicine, (2) perceived quality of the web-based clinical consultation, (3) satisfaction with telemedicine, (4) perceived professional productivity compared to traditional face-to-face visits, (5) willingness to use telemedicine after the pandemic, and (6) perceived barriers to telemedicine use. Data on these 6 components were gathered to understand the telemedicine experience better during the COVID-19 pandemic and to gain insights into the preparedness of the digital health care response for any potential crisis. We defined "acute remote care consultation" as any remote consultation made for the first time owing to an urgent medical complaint, the onset of a new disease, or a follow-up case that has not received a consultation for more than 6 months. Furthermore, "chronic remote care consultation" was defined as any remote follow-up consultation within 6 months of the initial in-person visit for a long-term medical condition [31].

Statistical Analysis

Differences between video and audio consultations were investigated using various outcome variables, which included 2 main parts. While the first set of outcomes was related to the perceived quality of clinical consultations, the second set of outcomes tested physicians' professional productivity with telemedicine over face-to-face consultations.

Descriptive statistics characterizing the study cohort were reported as frequency and percentage values for all variables. To compare the responses to our survey questions with regard to video and audio consultations, we performed chi-square analysis at a significance level of .05.

We used ordered logistic regression analyses to investigate the association between outcome variables and the modality, adjusting for confounding factors such as sociodemographic characteristics. A forced-entry approach was adopted to consider the variance inflation factor (VIF) diagnostic to prevent obtaining unreliable estimates of coefficients and odds ratios (ORs) owing to high correlations among predictor variables. Considering the high VIF for the variable of the number of years in practice (VIF>4), we excluded this variable and confirmed that multicollinearity is not a concern in the final models (VIF=1.51). Further, the Akaike information criterion was used to assess the fit of the models after excluding the variable of the number of years in practice. Survey questions were answered on a 5-point Likert scale where 5="strongly agree", 4="agree", 3="neutral", 2="disagree", and 1="strongly disagree". However, owing to limited observations toward the extreme ends of the scale ("strongly agree" and "strongly disagree"), we merged the responses of "strongly agree" and "agree" under positive responses and "strongly disagree" and "disagree" under negative responses together as these 2 statements were found to involve the same attitude continuum toward the question [32]; these were grouped under "disagreement," "neutral," and "agreement." The outcomes of the regression models were reported as ORs with 95% CI values, and $P<.05$ indicated significance. Statistical analyses were performed using STATA (version 16.1, Stata Corp).

Results

Overall, 623 physicians completed the survey, of whom 347 (55.7%) conducted only audio consultations and 276 (44.3%) conducted only video consultations during the COVID-19 pandemic. The sociodemographic descriptive characteristics of the 2 groups are summarized and compared in Table 1.

Table 1. Sociodemographic characteristics of the physicians included in the study (N=623) and descriptive statistics by modality.

Sociodemographic characteristics	Audio consultations (n=347), n (%)	Video consultations (n=276), n (%)	Total, n (%)	*P* value
Sex				.04
Female	163 (46.97)	107 (38.77)	270 (43.34)	
Male	184 (53.03)	169 (61.23)	353 (56.66)	
Age (years)				.52
≤39	87 (25.07)	59 (21.38)	146 (23.43)	
40-49	138 (39.77)	116 (42.03)	254 (40.77)	
50-59	83 (23.92)	62 (22.46)	145 (23.27)	
≥60	39 (11.24)	39 (14.13)	78 (12.52)	
Specialty				.23
Internal medicine	213 (61.38)	186 (67.39)	399 (64.04)	
Surgical specialties	38 (10.95)	22 (7.97)	60 (9.63)	
Family medicine	76 (21.90)	48 (17.39)	124 (19.90)	
Others[a]	20 (5.76)	20 (7.25)	40 (6.42)	
Physician designation				.13
General physician	62 (17.87)	41 (14.86)	103 (16.53)	
Resident	8 (2.31)	3 (1.09)	11 (1.77)	
Specialist	189 (54.47)	175 (63.41)	364 (58.43)	
Consultant	88 (25.36)	57 (20.65)	145 (23.27)	
Number of years in practice				.32
≤4	16 (4.61)	10 (3.62)	26 (4.17)	
5-9	52 (14.99)	33 (11.96)	85 (13.64)	
10-20	132 (38.04)	124 (44.93)	256 (41.09)	
>20	147 (42.36)	109 (39.49)	256 (41.09)	
Past experience with telemedicine				.09
Never used	256 (73.78)	219 (79.35)	475 (76.24)	
Used a few times	75 (21.61)	41 (14.86)	116 (18.62)	
Used frequently	16 (4.61)	16 (5.80)	32 (5.14)	

[a]Other specialties include speech therapy, dentistry, physical medicine and rehabilitation, anesthesiology, emergency medicine, occupational therapy, radiology, aviation and occupational health, periodontics, gynecology center, nutrition, urgent care, prosthodontics, and critical care medicine.

Sociodemographic Characteristics

Compared to physicians who provided audio consultations, those who provided video consultations were predominantly male (61.23% vs 53.03%, respectively; *P*=.04), middle-aged (40-49 years: 42.03% vs 39.77%, 50-59 years: 22.46% vs 23.92%, ≥60 years: 14.13% vs 11.24%; *P*=.52), and had a different specialty distribution with most belonging to internal medicine subspecialities (67.39% vs 61.38%; *P*=.23). Additionally, physicians who provided video consultations were mostly specialists with 10-20 years of experience in practice. In relation to previous experience with telemedicine modalities, there was a variation in responses. The majority of physicians who provided video consultations during the COVID-19 pandemic reported that they had never used this form of telemedicine previously, compared to their counterparts who provided audio consultations (79.35% vs 73.78%, respectively; *P*=.09); conversely, the proportion of physicians who reported frequent provision of video consultations was higher than that of their counterparts who provided audio consultations (5.80% vs 4.61%; *P*=.09).

Perceived Quality of Clinical Care Provided

Physicians' agreement with the following statements was assessed: (1) I was confident in managing acute conditions, (2) I was confident in managing chronic conditions, (3) I was able to answer my patients' questions, (4) I was able to provide health education to patients, and (5) I had an impression of misdiagnosis risk during the teleconsultation. The proportions of physicians who agreed, disagreed, or were neutral about the statements are indicated in Table 2**.** Overall, more than half of the physicians who provided video consultations agreed that they were confident in diagnosing acute conditions (*P*=.01), confident in diagnosing chronic conditions (*P*=.08), and able to provide patient health education during the clinical consultation, which was significantly higher than that of physicians who provided audio consultations (*P*=.006). However, there was no significant difference in the perceived risk of misdiagnosis (*P*=.41) and the physicians' ability to address the patients' questions (*P*=.26) among those who provided video or audio consultations. Remarkably, the proportion of male physicians who believed that telemedicine raises the likelihood of misdiagnosis was higher than the proportion of female physicians (*P*=.02) (Multimedia Appendix 1).

Table 2. Comparison of survey responses on the perceived quality of clinical care provided by modality.

Perceived quality of clinical care provided	Audio consultations, n (%)	Video consultations, n (%)	Total, n (%)	*P* value
Confidence in managing acute consultations				.01
Disagree and strongly disagree	85 (24.50)	47 (17.03)	132 (21.19)	
Neutral	121 (34.87)	85 (30.80)	206 (33.07)	
Agree and strongly agree	141 (40.63)	144 (52.17)	285 (45.75)	
Confidence in managing chronic conditions and follow-up consultations				.08
Disagree and strongly disagree	20 (5.76)	6 (2.17)	26 (4.17)	
Neutral	50 (14.41)	39 (14.13)	89 (14.29)	
Agree and strongly agree	277 (79.83)	231 (83.70)	508 (81.54)	
Ability to answer patients' questions				.26
Disagree and strongly disagree	9 (2.59)	3 (1.09)	12 (1.93)	
Neutral	36 (10.37)	23 (8.33)	59 (9.47)	
Agree and strongly agree	302 (87.03)	250 (90.58)	552 (88.60)	
Ability to provide patient health education				.006
Disagree and strongly disagree	15 (4.32)	1 (0.36)	16 (2.57)	
Neutral	36 (10.37)	24 (8.70)	60 (9.63)	
Agree and strongly agree	296 (85.30)	251 (90.94)	547 (87.80)	
Perceived risk of misdiagnosis with telemedicine				.41
Disagree and strongly disagree	47 (13.54)	35 (12.68)	82 (13.16)	
Neutral	84 (24.21)	80 (28.99)	164 (26.32)	
Agree and strongly agree	216 (62.25)	161 (58.33)	377 (60.51)	

Perceived Professional Productivity

The overall response to this survey section varied across the entire sample, with no significant difference in the physician-patient rapport among those who provided video or audio consultations compared to face-to-face consultations (*P*=.95) (Table 3). Interestingly, when compared to face-to-face consultations, the proportion of physicians who perceived that telemedicine reduces the overall documentation time (*P*<.001) and increases the total number of patient consultations (*P*=.01) was significantly higher among physicians who provided audio consultations than among those who provided video consultations. The proportion of female physicians who agreed that telemedicine decreases the overall documentation time and increases the total number of patient consultations was substantially higher than that of their male counterparts (*P*=.008 and *P*<.001, respectively) (Multimedia Appendix 1).

Table 3. Comparison of survey responses on perceived professional productivity by modality.

Perceived professional productivity	Audio consultations, n (%)	Video consultations, n (%)	Total, n (%)	*P* value
Patient's rapport rather than face-to-face consultations				.95
Disagree and strongly disagree	228 (65.71)	179 (64.86)	407 (65.33)	
Neutral	83 (23.92)	69 (25.00)	152 (24.40)	
Agree and strongly agree	36 (10.37)	28 (10.14)	64 (10.27)	
Reduced overall consultation time rather than face-to-face consultations				0.066
Disagree and strongly disagree	80 (23.05)	84 (30.43)	164 (26.32)	
Neutral	94 (27.09)	77 (27.9)	171 (27.45)	
Agree and strongly agree	173(49.86	115 (41.67)	288 (46.23)	
Reduced overall documentation time rather than face-to-face consultations				<0.001
Disagree and strongly disagree	84 (24.21)	104 (37.68)	188 (30.18)	
Neutral	77 (22.19)	77 (27.9)	154 (24.72)	
Agree and strongly agree	186 (53.6)	95 (34.42)	281 (45.1)	
Increased total number of consulted patients rather than face-to-face consultations				0.01
Disagree and strongly disagree	89 (25.65)	95 (34.42)	184 (29.53)	
Neutral	112 (32.28)	94 (34.06)	206 (33.07)	
Agree and strongly agree	146 (42.07)	87 (31.52)	233 (37.4)	

Working Experience, Satisfaction, and Barriers to Telemedicine

The majority of physicians who provided video consultations agreed that they received sufficient technological support during the web-based consultation; this proportion was greater than that of physicians who provided audio consultations (76.45% vs 53.60%, respectively; *P*<.001).

There was no significant difference in the satisfaction with the quality of the clinical consultation between physicians who provided video consultations and those who provided audio consultations (*P*=.07).

On assessing the barriers to telemedicine, physicians who provided audio consultations reported that the "inability to see the patient during the consultation" was a significant barrier to the quality of the remote clinical consultations (*P*=.001), and they preferred not to use telemedicine services owing to low payment and reimbursement rates (*P*=.004), were unable to confirm the patient's identity during the audio consultation (*P*=.04), and reported that lack of training is a barrier to the use of telemedicine services to provide remote care to patients (*P*<.001) (Multimedia Appendix 1).

Multivariate Analysis

In the multivariate regression model, video consultations were associated with significantly improved confidence toward the management of acute conditions (OR 1.62, 95% CI 1.2-2.21; *P*=.002) and increased perceived ability to provide patient education (OR 2.21, 95% CI 1.04-4.33; *P*=.04), while male sex was associated with a lower perceived ability to provide patient education during the web-based consultation (OR 0.48, 95% CI 0.27-0.84; *P*=.01). There was no significant difference in physician's confidence in managing chronic conditions or conducting follow-up consultations among those who provided audio or video consultations Table 4. Additionally, previous experience with frequent telemedicine consultations was significantly associated with higher confidence in diagnosing acute conditions (OR=2.12, 95% CI:1.04-4.33 *P*=.039) and with a lower perceived risk of misdiagnosis (OR 0.46, 95% CI 0.31-0.68; *P*<.001). Our analysis also shows that video consultations were significantly associated with a perceived increase in overall consultation time, overall documentation time, and a reduction in the overall number of patients consulted when compared to face-to-face clinical consultations. Previous experience with telemedicine was significantly associated with the perception of an enhanced physician-patient rapport and the perception of an increased total number of patient consultations when compared to face-to-face consultations (Table 5).

Table 4. Adjusted multivariate analysis for the perceived quality of clinical consultations.

Variables	Confidence in managing acute conditions		Confidence in managing chronic conditions and follow-up consultations		Ability to answer patient questions		Ability to provide patient health education		Perceived risk of misdiagnosis with telemedicine	
	OR[a] (95% CI)	*P* value	OR (95% CI)	*P* value	OR (95% CI)	*P* value	OR (95% CI)	*P* value	OR (95% CI)	*P* value
Modality (video vs audio consultations)	1.62 (1.2-2.21)	.002	1.35 (0.88-2.08)	.17	1.6 (0.94-2.74)	.08	2.02 (1.19-3.41)	.009	0.81 (0.58-1.12)	.20
Sex (male vs female)	0.84 (0.61-1.16)	.29	0.76 (0.48-1.20)	.24	0.57 (0.32-1.02)	.06	0.48 (0.27-0.84)	.01	1.23 (0.87-1.74)	.25
Age (years)										
40-49 vs <39	0.9 (0.6-1.36)	.62	1.16 (0.66-2.04)	.61	1.06 (0.52-2.13)	.88	1.66 (0.85-3.25)	.14	1.23 (0.8-1.89)	.35
50-59 vs <39	0.95 (0.6-1.51)	.83	1.53 (0.79-2.94)	.20	1.49 (0.67-3.33)	.33	1.34 (0.65-2.76)	.44	1.11 (0.67-1.82)	.68
≥60 vs <39	0.82 (0.46-1.44)	.49	1.7 (0.74-3.94)	.21	1.11 (0.43-2.92)	.83	2.17 (0.81-5.82)	.13	0.85 (0.47-1.54)	.60
Specialty										
Surgical specialties vs internal medicine	1.42 (0.83-2.41)	.20	1.06 (0.51-2.20)	.87	0.95 (0.41-2.19)	.90	1.42 (0.59-3.37)	.43	1.11 (0.62-1.99)	.71
Family medicine vs internal medicine	1.46 (0.92-2.32)	.11	1.38 (0.69-2.74)	.36	1.56 (0.61-3.95)	.35	1.26 (0.56-2.87)	.58	0.67 (0.42-1.09)	.10
Others vs internal medicine	1.52 (0.79-2.94)	.21	0.18 (0.09-0.37)	<.001	0.21 (0.09-0.49)	<.001	0.36 (0.16-0.84)	.02	0.54 (0.29-1.03)	.06
Physician designation										
Resident vs general physician	1.03 (0.33-3.19)	.96	0.74 (0.16-3.34)	.70	0.30 (0.06-1.47)	.14	0.66 (0.11-3.77)	.64	1.00 (0.31-3.23)	.99
Specialist vs general physician	1.34 (0.81-2.20)	.26	0.93 (0.46 - 1.87)	.84	0.70 (0.28-1.74)	.45	0.67 (0.29-1.57)	.36	1.20 (0.72-2.00)	.48
Consultant vs general physician	0.99 (0.56-1.75)	.96	0.48 (0.22-1.06)	.07	0.49 (0.17-1.36)	.17	0.57 (0.21-1.51)	.26	1.18 (0.65-2.15)	.58
Past experience with telemedicine										
Used few times vs never used	1.31 (0.88-1.93)	.18	0.79 (0.48-1.33)	.38	1.36 (0.69-2.70)	.38	1.43 (0.74-2.77)	.29	0.46 (0.31-0.68)	<.001
Used frequently vs never used	2.12 (1.04-4.33)	.04	1.37 (0.46-4.10)	.57	3.65 (0.48-27.63)	.21	1.26 (0.36-4.41)	.71	0.45 (0.22-0.91)	.03

[a]OR: odds ratio.

Table 5. Adjusted multivariate analysis for perceived professional productivity.

Variables	Patient rapport rather than face-to-face consultations		Reduced overall consultation time rather than face-to-face consultations		Reduced overall documentation time rather than face-to-face consultations		Total number of consulted patients rather than face-to-face consultations	
	OR[a] (95% CI)	*P* value	OR (95% CI)	*P* value	OR (95% CI)	*P* value	OR (95% CI)	*P* value
Modality (video vs audio consultation	1.07 (0.76-1.49)	.71	0.69 (0.51-0.93)	.02	0.48 (0.36-0.65)	<.001	0.66 (0.49-0.89)	.006
Sex (male vs female)	0.69 (0.48-0.99)	.04	1.00 (0.73-1.39)	.98	0.72 (0.52-1.00)	.05	0.60 (0.43-0.82)	.002
Age (years)								
40-49 vs <39	1.00 (0.64-1.56)	.99	0.75 (0.50-1.13)	.17	0.80 (0.53-1.20)	.28	0.81 (0.54-1.22)	.32
50-59 vs <39	1.40 (0.84-2.32)	.20	1.15 (0.72-1.84)	.56	0.89 (0.56-1.43)	.64	1.10 (0.70-1.76)	.67
≥60 vs <39	1.31 (0.70-2.44)	.39	1.25 (0.70-2.21)	.45	1.40 (0.78-2.53)	.26	1.26 (0.72-2.21)	.42
Specialty								
Surgical specialties vs internal medicine	2.03 (1.15-3.59)	.02	1.08 (0.64-1.81)	.78	0.94 (0.56-1.59)	.83	1.20 (0.73-1.97)	.48
Family medicine vs internal medicine	0.93 (0.56-1.53)	.77	1.30 (0.83-2.03)	.26	1.34 (0.84-2.15)	.22	1.19 (0.75-1.89)	.46
Others vs internal medicine	1.45 (0.74-2.84)	.27	0.74 (0.41-1.36)	.34	0.78 (0.42-1.44)	.43	1.22 (0.65-2.28)	.54
Physician designation								
Resident vs general physician	1.45 (0.46-4.63)	.53	0.97 (0.33-2.88)	.96	0.99 (0.3-3.25)	.98	0.76 (0.23-2.51)	.65
Specialist vs general physician	0.85 (0.51-1.43)	.54	0.99 (0.61-1.60)	.97	1.11 (0.67-1.82)	.69	0.91 (0.56-1.48)	.70
Consultant vs general physician	0.46 (0.25-0.86)	.02	0.61 (0.35-1.05)	.08	0.66 (0.37-1.17)	.16	0.59 (0.33-1.03)	.06
Past experience with telemedicine								
Used few times vs never used	1.46 (0.96-2.23)	.08	0.96 (0.66-1.41)	.85	0.96 (0.65-1.41)	.84	1.46 (0.99-2.14)	.05
Used frequently vs never used	2.49 (1.26-4.90)	.008	1.72 (0.84-3.54)	.14	0.80 (0.41-1.57)	.52	2.81 (1.38-5.71)	.004

[a]OR: odds ratio.

Discussion

Principal Findings

This analysis of 623 physicians shows that video consultations are independently associated with a 62% increase in confidence in managing acute conditions, and physicians who provided video consultations were 2-fold more likely to provide patient education during the web-based consultations. Moreover, previous experience with telemedicine was associated with a 2-fold increase in confidence in managing acute conditions and a 55% reduction in the perception of the risk of misdiagnosis. More than one-third (37.68%) of physicians who provided video consultations did not agree that telemedicine reduces the overall consultation time, and approximately one-third (34.42%) did not agree that telemedicine increases the overall number of patient consultations when compared to face-to-face visits. Additionally, those who had previous experience with telemedicine were 2.5-fold more likely to build a rapport with their patients and 2.8-fold more likely to perceive that telemedicine increases the total number of patient consultations when compared to face-to-face consultations.

The COVID-19 pandemic provided sufficient incentive for the health care system to shift to web-based care to minimize the exposure to SARS-CoV-2 [19,33] and ultimately, as reported by Portnoy et al, "the only virus one can get while doing telemedicine is a cyber virus" [34,35]. The presence of these different modalities of telemedicine provided different opportunities for patients to connect with their health care providers, with rapid implementation of video and audio consultations partially owing to the availability of smartphones and the ubiquity of videoconferencing apps, since cameras are now an essential feature of these cellphones [36-42].

Although data on physician experience and outcome quality with each modality are limited, our first key finding suggests that when evaluating a patient for the first time or a patient with an acute condition, there is an added value in using videoconferencing apps to evaluate the patient's general state of health, which is pivotal to the clinical decision-making process [43,44]. Because medical presentations can vary in acuity and thus warrant different management approaches, physicians may need a real-time modality to assess the patient better, view the site of pathology, discuss treatment options, address the patient's concerns, and promote compliance with the treatment regimen. Video consultations can proximate real-life visits to a great extent as both the physician and patient can interact with each other simultaneously; this negates the psychological distance by allowing facial expressions and body language to be observed and interpreted, thus promoting empathic communication and the generation of a physician-patient rapport [45]. Therefore, a video consultation may be preferable when consulting a new patient for the first time as physicians would feel more confident in making diagnostic and treatment decisions. However, when evaluating follow-up patients with chronic diseases or for medication refill, video and audio telemedicine may be of equal quality and have similar outcomes as reported here and in previous studies [35,46-48]. These results may also help policymakers in low- and middle-income countries in applying reasonable protocols for selecting either video or audio consultations for patients who live in geographically remote areas or those who require frequent follow-up evaluation [49]. For instance, video consultations could be used for new or mild-to-moderate clinical presentations where real-time evaluation is needed, while audio consultations could be reserved for follow-up patients with chronic medical conditions or those with nonurgent medical problems who need to travel long distances and incur out-of-pocket costs [50]. In this course, a double triage system may be needed where a triage nurse consults with the patient who requests a telemedicine appointment and assess the patient's triage level using the Triage and Acuity Scale before recommending an in-person visit or video or audio consultation for the patient [51].

Our second key finding is that previous experience with telemedicine was associated with a lower perceived risk of misdiagnosis. In this respect, the more physicians were trained on telemedicine, the more confident they were in making a clinical diagnosis and the lesser the impression of a medical malpractice they had. Our results emphasize the need to increase telemedicine competencies in residency training and other clinical programs. For example, it is important to provide a formal education on best practices on how to remotely assess a patient's chief complaint and vital signs and carry out remote physical examination before placing physicians in web-based clinics, as prior experience with telemedicine can increase readiness and preparedness to carry out web-based consultations. This is intuitive specially for physicians who frequently use telemedicine, including those involved in internal medicine and family medicine [52]. Our findings are consistent with those of previous studies [53-55]. Ha et al reported that physicians who had a structured educational program in telemedicine had greater confidence in addressing clinical problems than those who did not receive an educational program [56]. Furthermore, Moore et al reported that the lack of telemedicine training was a barrier to provide telemedicine services among family medicine residents [52].

Our third key finding is that video consultations were associated with a perceived increase in overall consultation time, increased documentation time, and decreased total number of patient consultations. It is plausible that video consultations lasted longer owing to several reasons including technical difficulties related to internet connection, poor audio or speaker quality, disruption to the conversation flow, and difficulties with guiding a remote physical examination. In face-to-face interactions, people see and hear each other's words as they are produced; however, when using videoconferencing platforms, actions and words are heard milliseconds later. These delays, although small, are meaningful and can interfere with the conversation flow and result in miscommunication, thus consuming more time in an attempt to understand patients' problems and physicians' instructions [14,57,58]. Moreover, during video consultations, the physician may guide the patient through remote physical examination, which may increase the duration of the clinical consultation. Subsequently, the total number of daily patient consultations is expected to decrease owing to an increased duration of consultations in a limited clinical schedule.

Our fourth key finding is the identification of elements that represent barriers to telemedicine. A physician's inability to see the patient during the remote consultation could restrict tele-examination of the patient, where a guided remote assessment of the underlying condition is not feasible owing due to limited interaction with the web-based interface and the patient's difficulty to follow clinical instructions without physically seeing the provider's technique [59]. Moreover, the inability to see the patient during the clinical consultation could raise serious security and privacy issues, since the physician may not be able to confirm the patient's identity during the remote consultation, thus emphasizing the need of guidelines on identity management and security considerations to protect the patient's privacy during both audio and video consultations. Additionally, reimbursement issues with audio and video consultations need to be acknowledged, as it does not appear to attract health care providers preferentially for the delivery of telecare services. The current payment plans have been confusing, as the telemedicine provider needs to consider different private and governmental insurance policies when providing a remote consultation [60]. This confusion has been also a major deterrent to the use of telemedicine services. Furthermore, the relative difference in cost between telemedicine visits and a comparable face-to-face visit has been one of the barriers to the use of telemedicine. If a telemedicine visit is remunerated at a lower value than an equivalent face-to-face visit, physicians would be less willing to increase the provision of this service. There is a need to establish standardized regulations and billing rules to control costs. In principle, reimbursement costs for teleconsultation need to be equivalent to those of face-to-face visits to increase the adoption of telemedicine services [60]. A lack of training on how to treat a patient remotely may also be an obstacle that jeopardizes the efficiency of the virtual consultations, which must be overcome by incorporating appropriate training curricula, which can be incorporated through physician training programs.

Limitations and Strengths

This study has several limitations that we intend to address in future studies. First, this was an observational study that reflects outcomes with video and audio telemedicine consultations at a single point in time. Second, data on what reimbursement challenges are associated with each modality was not captured in detail in this study, which might have biased physicians' attitudes toward each modality. Third, the perception of misdiagnosis was not defined in our survey; hence, it was challenging to understand the association between this outcome and predictors for physicians who used video or audio consultation. Fourth, in this study, patients' preferences for video or audio consultations were not captured and thus could have affected the number of clinical consultations for each modality and might have biased physicians' attitudes toward the mode of remote consultation.

Despite these limitations, our study has several strengths. To our knowledge, this study was one of the first comprehensive telemedicine studies in the Middle Eastern region, which had a nationally representative sample of physicians who used telemedicine and had a high survey response rate. Additionally, our study measured the difference in physicians' attitudes toward telemedicine by modality type, which is informative for policymaking decisions.

Conclusions

The experience with the COVID-19 pandemic has highlighted the important role of telemedicine in emergency responses. While we may not be able to precisely predict the exact diagnostic outcomes with each telemedicine modality, there is, however, a growing body of evidence that suggests that video consultations are associated with improved physician confidence in managing acute conditions and a greater ability to provide patient education during web-based consultations. This study demonstrates that when managing chronic conditions or follow-up patients remotely, audio consultation is as suitable as video consultation to health care providers. These findings may be helpful for health care policymakers in low-to-middle–income countries to provide ample health care access to patients with chronic and noncommunicable diseases. Previous experience with telemedicine was associated with improved physicians' confidence in case management, a lower perceived risk of misdiagnosis, an increased ability to provide patients with health education, and a better physician-patient rapport. Telemedicine services are likely to be retained, and as we build our telehealth system, it is intuitive to prioritize the "new normal" and implement a structured telemedicine curriculum in physician training programs and prepare them for web-based consultations. It is also necessary to acknowledge the barriers to telemedicine and create solutions and regulations to overcome these obstacles and increase the service adoption rate.

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Authors' Contributions

NA and BA conceptualized and designed the study. NA, BA, NB, MAA, RA, SAM, FAH, YAZ, and HA carried out the investigation and data curation. MCES, NA, and OCB performed the formal analysis. NA, MCES, BA, M Alhashmi, M AlGhatrif, NB, MAA, RA, and OCB drafted the manuscript. NA, MCES, BA, M Alhashmi, M AlGhatrif, NB, MAA, RA, SAM, FAH, YAZ, HA, and OCB critically reviewed and revised the manuscript. NA and BA undertook the administrative tasks related to the study. OCB, SAM, FAH, and HA acquired the funding for the study. All authors have read and agreed to the final version of the manuscript.

Conflicts of Interest

None declared.

Multimedia Appendix 1
Supplementary tables with additional results.
[DOCX File , 52 KB - medinform_v9i6e29251_app1.docx]

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Abbreviations

OR: odds ratio
VIF: variance inflation factor

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