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EARLY INTERVENTION SYSTEM CONTEXTUAL FACTORS CONTRIBUTING TO TREATMENT ATTENDANCE AND CLINICAL OUTCOMES

by

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A Dissertation

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Dedications

I sincerely appreciate Dr. Roberta Dihoff's guidance, patience, and help throughout this research. Her wisdom and support have significantly helped shape my professional identity. This dissertation is also dedicated to both of my parents, Shelley Eldridge and Anthony L. Stallworth, who have provided unconditional love and consistently reinforced my faith during my educational journey. Most of all, this dissertation is dedicated to the loving memory of my grandmother, Elizabeth Joan Jackson. Although she may have transcended this plane of existence days after my dissertation proposal, I am confident and comforted that she is watching over me with unwavering love and applause for this milestone achievement. Thank you all for everything.

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Abstract

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EARLY INTERVENTION SYSTEM CONTEXTUAL FACTORS CONTRIBUTING TO TREATMENT ATTENDANCE AND CLINICAL OUTCOMES
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Early Intervention Programs (EI) are an established method of addressing and treating earlier childhood developmental problems that involves a system of complex processes which families must navigate to secure and maintain care. Extensive wait times and multiple service providers burdensome caregivers which may impact treatment engagement. Telehealth offers some clinical utility for improving EI service provision. However, little is known how system contextual factors predict a child's Part B Eligibility and level of engagement with treatment. The primary aim of this study is to describe the effect that wait time, number of service providers, number of treatment services, and treatment modality on treatment engagement and clinical outcomes. The present study examined archival, program records from a participating Early Intervention Program (EIP). A total of 409 child EIP records were reviewed, treatment data were coded and analyzed. Multivariate regression analyses revealed significant predictive relationships between study variables on Part B Eligibility and treatment attendance. Clinical implications provide preliminary evidence regarding service provision of a NJEIS program to improve service wait time, number of recommended services, and telehealth options. Public health implications also offer valuable insight for understanding how EI healthcare system's contextual factors influence care utilization of families in New Jersey.

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Chapter 1

Introduction

Early Intervention and Prevention

Early intervention (EI) strategies are classified as any therapeutic process introduced during the early stages of development that is intended to mitigate the cognitive, emotional, or physical impact of a disorder or illness and improve overall functioning (Ramey & Ramey, 1998). For developmental disabilities, EI programs are often community-based, highly structured modalities that center on naturalistic environments and familial involvement (Nevill et al., 2018; Paynter et al., 2017; Vietze & Laz, 2020). EI programs have guidelines for service provision that, based on assessment conclusions, recommend eligibility that each child will receive during their care.

Although these standards vary across United States (U.S.) territories, EI programs typically include consecutive weekly hours of active, child-adult therapy and coaching based on goals determined from care educational plans, standardized assessment results, and manualized treatments (Hepburn, 2013; Hepburn, 2021). While these treatment characteristics encompass typical care experiences with EI, the common practices of the EI system, which include referral and enrollment process, also vary across states and regions (Fitzgerald et al., 2006; Pellecchia et al., 2021). The EI system includes services, state-to-agency referral processes, and regional resource for care provision (Monteiro et al., 2016; Wallis et al., 2020, Wise et al., 2010). The range of standards for both treatment modalities and system practices are a common research interest in the EI literature regarding clinical outcomes.

There is strong evidence for the effectiveness of EI programs that engage treatment starting early in childhood development (Alonso-Esteban & Alcantud-Marin, 2022; Landa, 2018; Harris & Haddleman, 2000). Weitlauf et al. (2014) conducted a systematic review of early intervention therapies for children with developmental disabilities and found earlier treatment engagement was associated with improvement in language and cognitive skills. Despite this, significant limitations of the present EI literature include the lack of randomized control trials, methodological inadequacy, and a lack of understanding of the best practices for EI system care delivery (French & Kennedy, 2017; Landa, 2018; Smith et al., 2015). These limitations contribute to the field's difficulty in ascertaining consensus on best practices for EI treatments and service provision approaches (Pellecchia et al., 2021).

Despite many EI modalities providing empirical supports for positive clinical outcomes, there remains a lack of consensus on which service practices are most effective and universally applicable to all child populations (Lord et al., 2022). An overview of reviews synthesizing the most current states of available, highest level of evidence for EI services found most customary recommendations for care before an evaluation are often not grounded in substantiated research evidence, such as number of hours a child should receive care, the number of care-providers needed to coordinate treatment, and modalities of treatment (Franz et al., 2022). Therefore, the variability of service implementation procedures and lack of strong science-based strategies typically defaults state administrators to establish best practices for EI service provision. This lack of standardization may leave opportunity for families to experience exhaustive care system navigation that may delay treatment during crucial developmental periods. Moreover, before treatment can be determined, EI system protocols require the child to meet qualifying criterion.

An official level of developmental delay is a common prerequisite to qualify for EI services and they vary across states (Ramey et al., 1998). Suspicion of a possible development delay, and the markers of when a diagnosis can be reliably determined, also varies depending on the developmental delay (Gargiulo & Kilgo, 2018; Herskind et al., 2015; Novak et al, 2017). While some states may determine engagement based on clinical suspicion, New Jersey does not permit suspicion for EI (New Jersey Early Intervention System, 2017). First detection or suspicion of a child's developmental delay is often noticed from the child's caregivers or primary care physician (Tsang et al., 2019). Navigation from first detection to EI evaluation, to enrollment, and then to engagement in EI services presents many challenges for caregivers that can lead to dropout or delayed early intervention during crucial development stages (Eisenhower et al., 2020). These steps are commonly referred to as the "process link" and present service obstacles for families to secure and retain EI care (Bagnato et al., 1997). Moreover, since caregivers are partially responsible for managing treatment and navigating this system, child engagement largely depends on how easily a caregiver can be retained throughout this process.

Federal regulations for EI under the Individuals with Disabilities Education Improvement ACT (IDEA) mandates that service details be established through collaborative efforts between the child's caregivers and service providers and should meet the needs of the child and family unit (Ravers & Childress, 2015). Therefore, state regulations and evidence-based treatment approaches focus on the parent – child relationship throughout the duration of EI service provision (Dragoo, 2019). According to a cross-sectional study on parental perception of family-centered approaches in EI services, caregivers demonstrated high investment in the family-centered nature of treatment services and higher treatment intensity was positively correlated with higher perception of treatment involvement from EI services (McManus et al., 2019). While the EI family-centered approaches offer greater clinical outcomes for children, caregiver demographics determine the ease of navigation, care management, and accessibility to resources needed to maintain enrollment and engagement with EI services. Little et al. (2015) identified several barriers that universally negatively impacts EI service acquisition and maintenance, such as poorly coordinated care, delayed service delivery after referral confirmation, and caregiver caution pertaining home-visits. These barriers indicate common problems of the EI system that could negatively impact family's engagement with care.

Cruciality of Timeliness and Treatment Engagement

From first detection of a need for professional intervention to actual service implementation, the time that a family waits for care is a crucial period (Miller et al., 2008). Since many developmental disabilities require support during the formative stages of development to gain the most clinical benefit, this period not only can delay therapeutic progress but also put certain family demographics at risk for attrition (Webb et al., 2014). Decades of research on models of service delivery for children with developmental delays have maintained that the earlier the delivery of care during development, the most effective and adaptive behavioral health outcomes can be (Anderson et al., 1987; Corsello, 2005; Harris & Handleman, 2000; Markryganni &

Reed, 2010). However, despite the evidence of the benefit of timely care implementation, many EI care systems maintain a difficulty with coordinating care within these time expectations which may lead to negative impacts in clinical health outcomes. A cohort study of 722 children, below the age of 3 years old, children receiving EI care found that over half of the sample received delayed services, with greater clinical severity being correlated with timely service coordination (McManus et al., 2019). Therefore, extensive wait times for caregivers throughout EI care coordination, especially in the earlier stages following referral when service providers are being assigned to a family, may result in a coordination bottleneck for the caregiver that makes it difficult to adequately engage with all services.

Longer wait times from initial detection to service provision is a well-documented risk for dropout during many pediatric treatment programs (Bisgaier et al., 2011, Gordon-Lipkin et al., 2016; Washington et al., 2019). For EI, industry problems such as lack of providers, costliness of care, and time-intensive evaluations have been found to explain how wait times remain a substantiated, persistent obstacle in the literature (Bisgaier et al., 2011; Kalb et al., 2012; Zablotsky et al., 2014). A survey of 90 practitioners found that longer times administrating evaluation assessment batteries was significantly associated with longer wait times for diagnoses and care linkages, with a median wait time of 7 months for families before receiving an evaluation (Penner et al., 2018). Moreover, there are mixed recommendations for appropriate wait times during care coordination with some guidelines establishing a maximum wait time of three to six months, and others not suggesting any time standards (Brian et al., 2019; Rutherford et al., 2018; Penner et al., 2018; UK, 2017). Considering the lack of profession consensus on acceptable wait times during the various stages of EI service coordination, studies have found that common wait times in some areas can be up to a year-long wait for an evaluation from the point of first detection (Austin et al., 2016; Iles, 2016). Ultimately, practitioners acknowledge that longer wait times can negatively affect opportunities for engaging in EI services and dismay caregivers during the process (Penner et al., 2018).

Efforts to establish adaptable actions to reduce wait times and improve treatment adherence have demonstrated some effectiveness. A longitudinal study evaluating an EI evaluation process of 2,076 toddlers found that a tiered system, encompassing community education, intensive-practice training, tailoring coordination practices to the needs of diverse communities, and community outreach, achieved a median wait time of approximately 2 months from initial detection to evaluation and service provision (Keehn et al., 2020). However, less is known about which part in the EI process link did caregivers tend to experience the most difficulty maintaining care. Since treatment engagement for the child is managed by the caregiver, engagement with scheduled EI appointments is a responsibility mostly held by families.

Reducing the wait time between evaluation to treatment implementation can mitigate negative health outcomes and markedly reduce the economic burden on caregivers (Zhou et al., 2021). In addition to this, caregiver’s attitudes throughout service acquisition and treatment processes appear to be a plausible consideration for EI system evaluations. A cross-sectional study examining caregiver’s attitude at different points of treatment coordination found parents who were satisfied with the quality of treatment during appointments, comfortable with established wait times, and content with their physician’s expertise were more likely to be satisfied with care (Gupta et al., 2022). Such findings provide implications for caregiver's perception of care and stressors throughout the EI service wait times. Considering that the EI system tends to have longer wait times and various barriers that caregiver providers must navigate to secure and maintain services, there is a dearth of research on what point in the process link are caregiver's more likely to experience stressors, have a change in perception of care, and are more likely experiencing difficulties attending with attending care.

Service Providers and Family Burden

Although wait times can be reduced, balancing numerous care providers and services throughout the EI treatment process can become burdensome for caregivers (Rutherford et al., 2018). Attitudes concerning timeliness of care implementation have been found to impact caregiver's perception of care and lead to further challenges with overall service provision (Loo et al., 2022; Towle et al., 2019). Furthermore, many recommended services are not readily accessible to many families depending on their region (Bisgaier et al., 2011; Kalb et al., 2012; Zablotsky et al., 2014). A study examining 223 caregivers experience with care found that only 40.8% had the required early intervention services in their area, with only approximately 8% being satisfied with them (Al-Mazidi & Al-Ayadhi, 2021). The process to securing EI treatment can be an obstacle for caregivers and each link during the process can present additional burden.

Communication regarding expectations during each stage of screening coordination, information about additional resources, and planning regarding the child's healthcare have been found to be common concerns from caregiver's that may influence stress and difficulty with managing care for the child (Cunningham & Rosenbaum, 2014; McManus et al., 2019, Ross et al., 2019). A study examining 102 parent's attitudes regarding the evaluation process found that lower family-provider collaboration and more professionals involved during the evaluation process was strongly associated with higher caregiver stress and burden (Moh & Magiati, 2012). Therefore, wait times and the number of services providers may contribute to a family's perception of EI care. Although families' experiences with care provision while waiting for an evaluation may be an integral factor to caregiver burden, less is known of how these predictors influence likelihood of service engagement.

Extensive EI service processes may deplete families of children with developmental disabilities of their emotional and financial capabilities. A mixed methods study of 31 parents of found that they experience depression and anxiety symptoms during the evaluation process for EI services and symptoms did not improve after enrollment (Myers et al., 2021). The Family Adjustment and Accommodation Resource (FAAR) model theorizes that family systems attempt to adapt to stress through an interactional balance of three domains: demands, meanings, capabilities (Patterson, 1998). "Demands" are conceptualized as external stressors or internal challenges that may evoke a significant amount of burden on the family's daily functioning whereas capabilities are the resources that a family must adequately address those demands (Carly Albaum et al., 2020; Patterson, 1998).

For families of children with developmental delays receiving or seeking EI services, the intensity of those demands may fluctuate as they navigate prolonged wait times, child behavioral wellness concerns, and multiple treatment providers. In response, FAAR suggests that families employ their "capabilities" through using their available resources (i.e., additional social support, parental education, supplemental support programs) to balance the demands. “Meanings”, in the FAAR model, are conceptualized to moderate this relationship as they include the protective values of family values, cultural identities, and worldview (Patterson, 1998).

According to the FAAR model, families enter a phase of adjustment when there is a pileup of demands that offsets the family present usage of capabilities. To address the imbalance, family’s access and appraise their family “meanings” to utilize or acquire more resources. Patterson (1988) argues that families are always exploring ways to maintain stability and the most common method is to acquire more capabilities to return to a homeostatic balance. Therefore, a family’s goal is to prevent a phase of maladjustment, or prolonged distressing imbalance, and achieve a phase of family adaption by exploring potential solutions (Carly Albaum et al., 2020; Patterson, 1998). Regarding EI, families may turn to services to help prevent this stage of prolonged challenge from ineffectively caring for a child with potential development disabilities.

Families with children of disabilities theoretically seek EI treatment as a potential resource to address the healthcare need of the child. However, if the process of navigating, acquiring, and maintaining EI treatment becomes a cumbersome demand, the family may have difficulty appraising EI services as an actual capability. It may become challenging to arrange, balance, or maintain appointments for their children, especially if there are multiple providers they need to coordinate with and extensive wait times for receiving care. Thus, for the family unit, a period of adjustment may lead to overall maladjustment to caring for a child with a developmental disability because the process intensified rather than mitigated their stressors. This can become increasingly salient for families with limited initial resources or from marginalized backgrounds. Ultimately, the complex and demanding responsibility of maintaining EI services may fundamentally cause more stress on the family unit.

Caregiver stress is a well-established predictor for treatment non-adherence across many pediatric populations (Kazin & Mazurick, 1994; Rovane et al., 2020; Werba et al., 2006). A caregiver's perceptions regarding the burden of treatment adherence on the family unit suggest that more time-demanding supervision of medication management, behavioral interventions, and other supplementary care can lead to reduced adherence to treatment (Hock et al., 2015). Furthermore, families with multiple service providers experience higher, disproportionate levels of stress and are more likely to have more unmet clinical needs (Lopez et al., 2019; Sloper & Turner, 1992). Thus, it is possible that navigating the EI system during service acquisition and maintaining enrollment during the treatment process can become time demanding. Comparatively, especially when considering the variability of wait times during EI service coordination and screenings, the process may become disproportionately onerous to manage depending on the number of providers a family must balance to maintain care.

Depending on a child's presenting clinical problem for EI, they are recommended specific providers to address the concerns. Although more service providers offer additional clinical methods to addresses the child's unique needs, balancing more service providers appointments may negatively impact the family's appraisal of its usefulness. Bruder and Dunst (2004) national report on the helpfulness of early intervention services found that the more providers involved with a child's care, the less the family found the services to be helpful. More providers involved in a child's EI service provision can be also burdensome at various stages of EI care. A study of 190 families of children enrolled in EI services for at least 1 year found families with one provider had significantly less reported stress compared to families with more (Shonkoff et al., 1992). Moreover, studies have also found that children with less providers also achieve greater clinical gains throughout EI care and sustain clinical outcomes well after completion of EI services (Shonkoff et al., 1992; Woodman et al., 2015; Woodman et al., 2018). The number of service providers involved with a family's EI care does negatively impact stress, but less is known of how this may influence service engagement.

Economically disadvantaged and racial/ethnic minority families are more likely to report higher levels of caregiver stress, challenges ascertaining care, and difficulty adhering to processes of treatment (Trentacosta et al., 2018). There are many factors that make engaging in EI treatments particularly burdensome for cultural minorities that are also of relevance to examining the effectiveness of the EI system. Care expenses also can vary depending on developmental diagnosis which can influence the potential financial impact that balancing care can have on a family unit. For example, Lavelle et al. (2014) examined data from three national medical expenditure datasets and estimated the annual expenses of caring for a child with autism spectrum disorder (ASD) is roughly $17,000 when factoring costs for education, behavioral treatments, and medical costs. Extensive coordination and facilitation of care for a child with a developmental disability may become a financially straining responsibility for caregivers that limits capacity for treatment engagement. Studies have found that longer commutes to treatment, full-time parental employment statuses, and lower socioeconomic status (SES) predicted lower likelihood for enrollment and risk for dropout of clinical trials for children with development delays (Bradshaw et al., 2020). Although such implications extend to research settings, these predictors may suggest possible treatment interferents in EI care in the community.

Sapiets et al. (2021) reported a need to focus on the intersection between EI service provision and family factors to improve the barriers to service provision, including improving access to reduce exhaustive wait times and treatment interfering barriers. Within this focus, telemedicine services are argued to be a useful tool to increasing accessibility and improving satisfaction with healthcare services (Atmojo et al., 2020). Specifically, regarding pediatric healthcare, telehealth services have demonstrated effectiveness in reducing total healthcare costs for caregivers, increasing overall satisfaction with healthcare services, and reducing hospitalizations (Ferro et al., 2021). Telehealth has also been found particularly effective at reducing the amount of time to treatment commencement for many medical pediatric populations (Gali et al., 2022; Solomon & Soares, 2020). Similar to telehealth's usefulness in service delivery and its potential for improving family's experience with pediatric healthcare, telemedicine has some advantages in EI service provision.

Telehealth for Early Intervention Service Provision

Promotion of telehealth as a more accessible, convenient vehicle to service administration has led health disciplines to consider technology-based care as a reasonable alternative to traditional treatment practices (El-Miedany et al., 2017; Galpin et al., 2021; Sherperis et al., 2021). Telehealth, a term interchangeable with telemedicine, is defined as any treatment intervention, screening, or service that is administered from a provider to a patient via electronically based communication devices (Tuckerson et al., 2017). These electronic communication vehicles can include videoconferencing or phone calls. Telehealth has become ubiquitous across health disciplines, with a significant surge to balance the COVID-19 pandemic demand of healthcare with the cautions of social distancing (Garfan et al., 2021; Koonin et al., 2020). Telehealth screening and treatment modalities for child populations have demonstrated clinical usefulness in service delivery (Brophy, 2017).

EI services often utilize face-to-face, provider-family assessments and interventions with some rural areas typically using telehealth services due to limited local, in-person service availability (Ashburn et al., 2014; Baharav & Reiser, 2010; Brophy, 2017; Casin, 2009). Equitable and effective usage of telehealth service modalities has been a point of research interest for its clinical utility for decades (Clark et al., 2010; Jelinek et al., 2022). Research on whether face-to-face or telemedicine services offer superior clinical outcomes continue to be explored throughout the literature as new treatment modalities are established. Sutherford et al. (2018) conducted systematic review of studies of children with development disabilities receiving technology-based treatment and found no differences between face-to-face and telehealth modality in assessment, speech therapy, and early intervention care. In addition, a study examining technology-enabled interventions for children with developmental disabilities found no significant differences in service reception between face-to-face versus remote interventions, with remote interventions demonstrating significant improvements in fidelity, play diversity, and joint attention (Shire et al., 2020). These findings provide evidence to telemedicine being used as an alternative, or supplemental, resource for EI service provisions.

Telemedicine may improve caregiver satisfaction and perception of care when receiving EI services. Little et al. (2015) identified several barriers that universally negatively impacts EI service acquisition and maintenance, such as caregiver caution pertaining home-visits. To address this caution, telemedicine may be a reasonable alternative to care to address EI barriers to care by helping families feel more comfortable with services not requiring a home-visit. Telehealth has been found to increase parental self-efficacy and service satisfaction for parents receiving care for children with developmental delays (Owen, 2020). One study evaluated telehealth EI coaching during a nine-week period of treatment of 17 families and found significant gains in child performance, treatment goal attainment, and parental satisfaction compared to face-to-face alternative (Kronberg et al., 2021). Telehealth alternative during EI service delivery may provide a flexible alternative to face-to-face treatment for families with changing needs. Additionally, telehealth pediatric care has been found to increase accessibility which may address some of the health inequalities observed in the EI literature (Jelinek et al., 2022).

Mixed findings on telehealth usefulness in addressing health inequity in treatment settings exist in the literature. Telemedicine has shown to reduce health inequities by extending healthcare access to marginalized, remote, and underserved populations (Brophy, 2017; Casin, 2009). Studies have shown telemedicine screenings can reduce economic burdens for lower SES families and increase accessibility for rural families (Juarez et al., 2018). However, the digital divide, which refers to a gap in access and application of modern technological communication devices, may impact a family's ability to incorporate telehealth into their lifestyles (Hoffman, 2022). Families who are lower income, live in rural settings, and are non-English speaking, or have lower education or literacy are more likely to be negatively impacted by the digital divide (Aylward et al., 2021, Berger et al. 2022). Likewise, unanimous preference and adequate evidence for EI service administration of telehealth-based care in EI remain unclear (Yang et al., 2021).

Though there exists much potential benefit for EI telehealth services, additional mixed findings on family and provider preference compared to face-to-face visits remain. For example, Yang et al. (2021) conducted focus groups on 37 families with children with disabilities and found that caregivers preferred in-person EI home visits compared to telehealth despite recognizing the benefits that it offers to promoting accessibility and communication. In addition, another study examining a family reception of state's EI programs telediagnosis assessments found that a significant majority preferred in-person visits compared to telemedicine (Jones et al., 2022). Furthermore, literature on EI providers preferences demonstrate similar mixed results. Some EI providers have been shown to prefer in-person treatment visits to better assess skill development, understand aspects of the child's natural environments, and more securely provide an adequate diagnosis (Ashburn et al., 2016; Cole et al., 2019; Juarez et al., 2018). Differences in preferences for caregivers may reflect differing family needs, resources, or demands. However, there is a paucity of research explaining how telemedicine for EI services may influence likelihood for clinical improvement throughout the EI process link.

Telemedicine appears to offer an alternative option to clinical service delivery for early intervention, but little is known how on how it may influence service provision. Similarly, findings indicating that shorter wait times and less service providers may positively influence family's perception of EI care offer little implications to whether it also directly impacts likelihood of treatment attrition or clinical progression (Bruder & Dunst, 2004; Lopez et al., 2019, Woodman et al., 2015; Woodman et al., 2018). Since each state's EI systems operate differently while adhering to federal standards, studies have recommended that these factors should be examined within the context of a state's specific service provision (Fitzgerald et al., 2006; French & Kennedy, 2017; Landa, 2018; Pellecchia et al., 2021, Smith et al., 2015). New Jersey offers a feasible starting point in evaluating how these factors may predict EI dropout and clinical outcomes due to relatively superior geographical, racial, and economic diversity compared to many other states (U.S. Census Bureau, 2021).

New Jersey's Early Intervention and Prevention

New Jersey's Early Intervention System (NJEIS) is a state-funded body, under the New Jersey's Department of Health, that manages the standards of EI care of contracted public and private agencies providing referral, treatment, and other avenues of care for children under the age of 3 years old (New Jersey Early Intervention System, 2017). Children within this age range, must meet the evaluative criteria of living with developmental delay or a condition with high probability to be eligible for EI services (New Jersey Department of Health, 2015). The condition with high probability criteria is described as physical or mental condition that has a significant likelihood of resulting in a developmental delay (New Jersey Early Intervention System, 2017). Before care is commenced, the NJEIS has created a series of policies and procedures that provide guidance for both program providers and families. These policies are informed by federal regulations and describe care coordination sequences for obtaining services for a child.

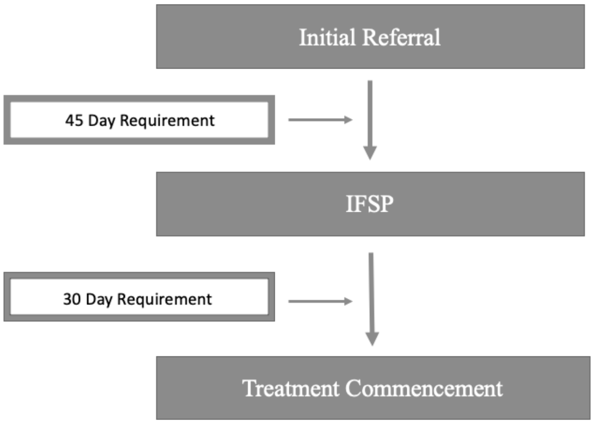
In the context of New Jersey's Early Intervention Program (EIP), "Part B Eligible" typically refers to eligibility for services under Part B of the Individuals with Disabilities Education ACT (IDEA) (Garda, 2006). New Jersey Early Intervention System, 2017). Part B of IDEA covers the provision of special education and related services for children and youth with disabilities aged 3 through 21 (Garda, 2006). When a child is deemed "Part B Eligible" in the context of EIPs in New Jersey, it means that they meet the eligibility criteria outlined in Part B of IDEA and may qualify for special education and related services provided by their local school district or educational agency. This eligibility determination is typically an evaluation process, which may include assessments and other calculations to determine the child's eligibility for special education and related services based on specific disability categories and educational needs.

There are many stages a family encounters throughout the NJEIS system to secure and maintain services, and ultimately receive a determination for Part B eligibility. According to the NJEIS's referral system point of entry, Regional Early Intervention Collaboratives (REICs) are regionally based system points of entry (SPOE) for referral to the NJEIS based on the county of residence (New Jersey Department of Health, 2015). Under these SPOEs, each REIC adheres to state approved referral procedures and reports timelines after families first point of contact to the NJEIS. To be considered referred in this system, caregivers must contact the REIC SPOE and/or is identified by a primary referral source (i.e., physician, childcare programs, social service agencies, etc) (New Jersey Department of Health, 2015). Next, the REIC assigns a service coordinator that contacts the caregivers within 2 business days of the referral date to collaborate and schedule an evaluation (New Jersey Department of Health, 2015). Once decided, the service coordinator forwards the family's information to a Target Evaluation Team (TET) which conducts the initial assessment and evaluation.

Within 45 days of initial referral, a multidisciplinary evaluation of the referred child and the initial Individualized Family Service Plan (IFSP) must be completed (see Figure 1) (New Jersey Department of Health, 2015). During this time frame, the TET initiates contact with the family to coordinate an evaluation. In the case of a family not responding, a series of outreach protocols could last up to 15 days until the system closes the referral (New Jersey Department of Health, 2015). This point of the NJEIS process link is crucial for service and treatment planning because the IFSP details how EI services will be provided to the family thereby providing an expectation of care.

Figure 1

NJEIS Process Link from Initial Referral to Treatment Commencement



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The IFSP has been a central focus for theoretical and practical debate in the EI literature since it is an opportunity for the caregivers and service providers to collaboratively develop an action plan for EI service provision (Bernheimer et al., 1990; Goodman & Hover, 1992; Rutland, 2022). Also, the evaluation, which includes the Battelle Developmental Inventory II (BDI-II), NJEIS's identified standardized assessment measure for child development, offers clinical insight into the child's functioning and areas for possible intervention (New Jersey Department of Health, 2015). TET must schedule this evaluation within 22 days of the receipt of the referral and, in the case of not being able to meet this deadline, must contact the SPOE (New Jersey Department of Health, 2015). Reasons for delay during this 45-day period is required to be documented within the child's record.

The point from IFSP to treatment commencement includes the family being assigned service providers which may vary depending on the clinical evaluation. Early Intervention Program (EIP) assignment is assisted by the service coordinator following the IFSP (New Jersey Department of Health, 2015). The service coordinator navigates a list of EIP's and communicates with these programs to assess each programs capability of providing comprehensive care for the identified family. The REIC coordinates with EIP agencies to decide who will be able to total needed services as identified by the IFSP and evaluation (New Jersey Department of Health, 2015). There are many circumstances during this point that can extend the wait time for families. For instance, the service coordinator may request additional assessments which may prolong this point in the process link.

Since New Jersey (NJ) does not follow a primary service provider (PSP) approach, one allocated service provider that acts as the primary support to the family, the caregiver is expected to balance and coordinate each visit and treatment with all recommended service providers (Sheldon & Rush, 2013). According to NJEIS's process link, the point from IFSP to treatment commencement should not exceed 30 days (see Figure 1) (New Jersey Department of Health, 2015). However, if EIP assignment is extended past 30 days, the REIC service coordinator units electronically broadcast to all potential EIPs until services are secured (New Jersey Department of Health, 2015). Treatment commencement is considered met when at least one of the services included in the IFSP coordinates with the caregiver.

The United States' Department of Education requires NJEIS to produce a State Performance Plan that complies statewide data into an annual performance report. The first required indicator is an analysis on the state's timeliness in provision of services. The annual target for this indicator is 100% and for the 2019 Federal Fiscal Year (FFY), New Jersey (NJ) reported a 96.08% indicating that the state did not meet its target (New Jersey Early Intervention System, 2021). Since 2013, NJ's FFY has ranged from 93.13% to 97.56% which suggests that the state has failed to meet their target for timely receipt of services for EI families (New Jersey Early Intervention System, 2021). To address some of the timely provision, this report reviewed statewide telehealth services. Since in-home services after COVID-19 disruption to care standards, 40-45% of IFSP services per week were reported in-person, 60-55% were telehealth, and 100% service coordination's were remote (New Jersey Early Intervention System, 2021).

According to the State Performance Plan Annual Performance Report, NJ's digital divide has affected the reception of NJEIS's tele-based EI services (New Jersey Early Intervention System, 2021). Prior to COVID-19, many families were using publicly available internet services, such as free WIFI at library's, to engage in telehealth services (New Jersey Early Intervention System, 2021). Also, prior to COVID-19, NJEIS provided supplemental funding and equipment to increase technological access for families affected by the digital divide. However, since COVID-19 has further impacted this accessibility, many families still reported difficulty remotely engaging in services (New Jersey Early Intervention System, 2021). Furthermore, families reported significantly higher satisfaction with NJEIS service prior to COVID but there was little information on what influenced the shift in satisfaction (New Jersey Early Intervention System, 2021). Despite telehealth being offered to families, NJ reported that 4% of families disenrolled in care and an 87% decrease in overall referrals to care compared to pre-COVID rates (New Jersey Early Intervention System, 2021).

Theoretical Framework: Healthcare Utilization

There are many frameworks that address individual and family system contextual factors, but most have not explored those relationships in healthcare utilization. Hong, Tauscher, and Cardel (2017) proposed a conceptual framework model that aims to describe the unidirectional relation between individual characteristics, health services quality, contextual factors, and health service utilization. The authors presented modifications to Ronald M. Anderson's Behavioral Model of Health Services, a widely used framework for understanding health service utilization dynamics, to allow specific portions of the framework to be isolated and evaluated (Anderson et al., 2011; Hong et al., 2017). Hong et al. (2017) model explains that individual factors can impact both healthcare service quality factors and healthcare utilization factors separately while healthcare service quality factors can only effect healthcare utilization outcomes. In addition, within each subdomain (e.g., health services quality contextual factors) are additional subsets (e.g., access to care) that further explains various aspects that can be conceptualized. Using the framework from this model, access to care explains how a family's ability to use, and their ease of use, of a specific care system will be directly related to utilization of that healthcare service.

For the current study, access to care was conceptualized as NJEIS program's wait times, services assigned to families, service agencies involved with care, and the modality of treatment. Previous literature demonstrated that wait times and services directly affect a family's perceived burden and perception of ability to engage with EI care (Gast et al., 2020; Murayama et al., 2017). Furthermore, the FAAR model offered supplemental theoretical rationale to how wait times and number of services involved with a child's care can increase demand and deplete a family's resources. Services provided via telemedicine, or in-person modalities, can influence a family's ease of access, but this may depend on the family's appraisal of its usefulness.

Although this model indicated that access to care is a contributing theoretical factor to utilization, the method that early intervention delivers this care may complicate this access. For instance, if a child is assigned three service providers that a parent is required to balance appointments with then accessing these various levels of care does not fit the family's demands. Furthermore, extended wait times at various points in the process link may foster additional challenges with their ability to use the health services.

In consideration of this theoretical framework, there appears to be a paucity of research literature that examines how these factors may predict treatment engagement and clinical outcomes for EI programs.

Aim of Present Study

The present study had two main aims to understanding service factors that impact patient outcomes. The first aim of this study was to better understand whether certain service quality factors influence patient engagement with care. We hypothesized that children that have greater number of service providers assigned to their case, experience longer wait times, and have more in-person sessions will have greater dropout and higher lack of engagement. The second aim of this study focused on the same predictive EI service quality factors but evaluate whether they impact child clinical outcomes and treatment dropout. For this, we hypothesized that children with greater wait times, more telehealth services, and less providers assigned to their case to have greater clinical outcome. Therefore, the following research questions as corresponding hypotheses are:

1. Research Question #1: Does wait times, number of service providers, number of services and treatment modality predict treatment attendance?

a. Hypothesis #1: Longer wait times, more service providers, more services, and less availability of telehealth options predicts less treatment attendance.

2. Research Question #2: Does wait times, number of service providers, number of services and treatment modality predict part B eligibility?

a. Hypothesis #2: Longer wait times, more service providers, the type of treatment modality predicts higher likelihood of being part B eligible.

Chapter 2

Method

Procedure

This study utilized archived patient care data exclusively obtained from EIP in southern New Jersey. Approval for data usage was obtained from the participating agency's Institutional Review Board and the New Jersey Department of Health. Approval for the study was obtained from the Institutional Review Board of Rowan University. Program data were accessed through the program's data management software. Prior to analysis, the archival data were reviewed to ensure consistency and the completeness of recorded information. Data spanning three years, from March 2020 to March 2023, were analyzed.

Participants

The study included infants and children who received services through Rowan University's EIP. Inclusion criteria were infants and children who received care through NJEIP and completed services during the specified period, while exclusion criteria included participants still enrolled after March 2023 or those who discontinued were prematurely. Of the initial 545 participants, 136 (16%) were excluded for not meeting these criteria. The remaining 409 participants constituted the final sample. In our sample, most participants were White (42.29%) and male (83.61%), with an average age of 19.61 months (M = 19.61, SD = 6.3).

Research Design

The study employed a retrospective observational design, utilizing archived patient care data from Rowan University's EIP. While not a secondary data analysis in the traditional sense, the clinical data had been previously documented by practitioners in the record. Ethical considerations were addressed through approvals obtained from relevant institutional review boards. Measurement integrity was ensured by reviewing data for changes in measures and treatment attendance criteria. The research design adhered to ethical guidelines and standards for data use and analysis.

Measures

Demographics

Demographics were collected by identifying the characteristic indicators of the child documented in their EIP record. For this, the child's race and age at the time of enrollment to the specific EIP was collected.

Eligibility

In the context of NJEIS, "Part B Eligible" typically refers to eligibility for services under Part B of the Individuals with Disabilities Education ACT (IDEA). Part B of IDEA covers the provision of special education and related services for children and youth with disabilities aged 3 through 21 (Dragoo, 2017). When a child is deemed "Part B Eligible" in the context of EIP in New Jersey, it means that they meet the eligibility criteria outlined in Part B of IDEA and may qualify for special education and related services provided by their local school district or educational agency. This eligibility determination is typically an evaluation process, which may include assessments and other clinical techniques to determine the child's eligibility for special education and related services based on specific disability categories and educational needs. Eligibility was dichotomously coded indicating whether a child was Part B eligible or Part B ineligible.

Treatment Planned

For this value, the number of treatment days agreed upon on the IFSP. For treatment attendance, the number of hours that the caregiver presented the child for treatment with a service provider was counted and the total was be compiled. Since each child's IFSP indicates the specific number of encounter hours that the child is recommended be engaging in care, the number was extracted from the child's record and multiplied by the number of weeks of planned services. For example, if a child engaged in care for 7 months (28 weeks) and was planned for services 3 times a week, then 3 would be multiplied by 28 weeks to determine the total number of days of treatment required. This value was coded numerically.

Treatment Attendance

For treatment attendance, the total number of billed service encounters within the participant records were extracted from billing records was coded as treatment attendance. Practitioner cancelations and IFSP meetings were omitted from this value. This value was coded numerically.

Services

Recommended services ranged depending on the child's developmental needs and are documented in the initial IFSP. Services were calculated by the number of services recommended which could have included separate service type by location, home, daycare, and delivery method (i.e., in-person or telehealth). This documented number of services recommended services were extracted from the electronic record for each observed case from the child's IFSP and represented this variable's value. These services included speech therapy, occupational therapy, physical therapy, developmental intervention, social work, and family training. This value was also coded numerically.

Service Provider Program (SPP)

This variable represented how many agencies offering care were attached to the family's care. This value may differ slightly from the number of services in the record. For instance, a child could have two services recommended at IFSP, but one provider program picked up both services. SPPs were extracted from the electronic record for each family. This value was coded numerically.

IFSP Wait Time

The days from referral to initial IFSP were calculated. This value was coded numerically.

Service Wait Time

The days from IFSP from to the commencement of all services were calculated from the record. This value was coded numerically.

Modality

All child records indicate whether services have been administered via telehealth or in-person. If a child received only telehealth service encounters with a provider, it was coded as “Telehealth”. If a child received no telehealth service encounters and had only received in-person, face-to-face visits, then it was coded as “In-person”. Services were coded combined if both modalities were used and coded “Combined”.

Analytic Strategy

Preliminary Analyses

We used G*Power 3.1 software to calculate an a priori power analysis to suggest our target sample size using our proposed count regression model (Faul et al., 2007). A sample size of 113 participants affords a power of 0.95 to detect an effect size of $f^2 = 0.04$ given our five predictors and an $a = 0.05$. Descriptive statistics evaluated age and race of the child. Basic, quantitative characteristics of the sample is presented using the means, percentages, and standard deviations. Descriptive and frequency statistics were used to examine all our primary study variables and demographic variables. Correlations of all variables were computed.

Main Analyses

R Statistical Package software was used for our regression analyses. We conducted two individual regression analyses to (1) predict treatment attendance and (2) Part B eligibility. For both of our regression models, the predictor variables remained the same (i.e., IFSP wait time, service wait time, modality, service provider programs, and services) and control for age. Because age presented a possible confound in understanding our outcomes, it was controlled for its effects to get a better model for the direct impact that our predictors have. Therefore, each regression model includes the same five predictor variables.

For our first hypothesis, a negative binomial regression was appropriate for our research question because it is effective at addressing over-dispersed count variables (Hilbe, 2011). Our outcome variable of days attended is a count variable. We expected over-dispersion, which is higher conditional variance compared to conditional mean, to occur because the variable nature of patient attendance (i.e., some patients attending treatment disproportionately more than others) is likely not to be equal to the mean of all patient attendance (Hilbe, 2011). For number of attended treatment days, we expected the variability to be much higher than the mean because past EI literature evaluating attendance demonstrated similar patterns when patient attendance had large variances (Bayer et al., 2008; Brookman-Freeze et al., 2008; DeGuzman et al., 2021). Therefore, it was very likely we would observe similar overdispersion instances in our outcome variable.

To account for the probable over-dispersion of these conditional distributions with count data, a negative binomial regression added an additional parameter compared to a Poisson regression (Hilbe, 2011). This model also included an offset variable of the number of days a child was planned to engage with care. Because some children enrolled in EI services are expected to engage with more care than other children due to their presenting concern and treatment recommendations, our model’s inclusion of an offset variable (e.g., required days according to treatment plan) accounted for this proportional observation (Hilbe, 2011). Further, binary coding, specifically dummy coding, was used to translate our categorical variable of modality in our model. For modality's dummy coding, "In-person" was placed as the reference category. Therefore, the coefficient for "In-Person" was absorbed into the intercept term of the regression model, and the coefficients for "Combination" and "Telehealth" represent the change in the outcome variable relative to the baseline level when the color is "In-Person" (Daly et al., 2016).

Multicollinearity was assessed between the predictor variables of these models by checking the Variance Inflation Factor (VIF) to evaluate whether they are significantly different from one another and prevent overinflation of standard errors (Cohen, 2015; Daoud, 2017). Goodness-of-fit statistics were examined to determine how well both models fits our data. Because the R package we used, MASS, produces estimates that included a nested Poisson model to check our model's assumptions, we also conducted our model as a Poisson and compared chi-square value estimates to provide further evidence for which model is best (Ripley et al., 2013). Regression coefficients, confidence intervals, and p values were evaluated to describe the relationship between the predictors and outcome variables. In addition, incidence rate ratio (IRR) were calculated to understand the strength and direction of the effects of predictor variables on the outcome variable, particularly in the context of count data analysis with overdispersion (Bennet, 2018). Thus, our proposed model for our first hypothesis was:

$$log\colon \frac{Treatment\ Attendance}{Treatment\ Planned} = \beta + \beta_1 x \text{IFSP wait time} + \beta_2 x \text{Service wait time} + \beta_3 x \text{Service provider} + \beta_4 x \text{Services} + \beta_4 x \text{treatment modality} + \text{u.}$$

For the second hypothesis, we used a logistic regression due to its appropriateness for modeling binary outcomes for the outcome variable of ineligibility for Part B services (Menard, 2002). Furthermore, a logistic regression was used to estimate the probability of a participant being ineligible for Part B services based on each of our predictor variables. For the assumptions of linearity for each predictor variable in our model, a Box-Tidwell test was used to determine which variables either met logistic regression assumptions or required transformations (Kay & Little, 1987; Mat Roni et al., 2020). A Hosmer-Lemeshow test was also used to examine our model's goodness-of-fit was performed to ensure our model adequately reflected the observed data (Menard, 2002). Pseudo R2 statistics, including Nagelkerke and McFadden's R2, were calculated to understand the explained by the logistic regression model. VIF for each predictor variable to quantify the degree of multicollinearity, with values greater than 5 or 10 considered indicative of multicollinearity (Daoud, 2017).

Once this model was created, regression coefficients and Odds Ratios (OR) were interpreted to explain the effects of each predictor variable on the likelihood of a child being ineligible for Part B services. The significant predictors were identified by examining the regression coefficients, confidence intervals, and p-values. Next, we used model comparisons to determine the magnitude of coefficients and odds ratios of the most influential factors associated with ineligibility. Dummy coding was used again to transform the categorical predictor variable of treatment modality and the binary outcome variable of eligibility in this model. Also, multicollinearity was again assessed between the predictor variables of these models by checking the Variance Inflation Factor (VIF) to evaluate whether they are significantly different from one another and prevent overinflation of standard errors (Cohen, 2015; Daoud, 2017). Therefore, our proposed model that for this question is:

$$Part\ B\ Ineligibility = \beta_0 + \beta_1 x \text{IFSP wait time} + \beta_2 x \text{Service wait time} + \beta_3 x \text{Service provider} + \beta_4 x \text{Services} + \beta_5 x \text{treatment modality} + \text{u}$$

The multiple R^2 squared, adjusted R^2, and p values were evaluated to provide the estimates of our entire model. Additional emphasis was used when evaluating the adjusted R^2 because this value increases with the number of predictors added to the model providing a better estimate of variance for multiple regressions (Osbourne & Waters, 2002). Nevertheless, we evaluated both R^2 to determine the extent our predictor variables variance explain the extent of our outcome variables variance. The p value determined statistical significance of the model. Next, each predictors regression coefficient, standard error, and p value was evaluated to determine which variable predicts clinical outcome.

Odd Ratios (OR) were examined to determine the degree and direction of the relationship between the predictor variables, the log odds of the outcome variable, and obtain a more interpretable measure of effect size compared to regression coefficients alone (Sperandei, 2014). Cross-validation was used to obtain the predicted probabilities, determine how well the logistic regression model generalizes to new data and identify any potential issues with overfitting or underfitting (Krstajic et al.,2014; Olsen, 2024).

Finally, for both models, considering much of our data is archived program service records and the fact that we are unlikely to capture other impactful variables, we account for the possibility of unaccounted confounds. For example, parental stress and caregiver satisfaction may be a confounding variable that may be relevant to our model, but we do not have access to measuring this for our proposed study. Therefore, we conducted a sensitivity analysis to determine the probable effect a confound would have to be to significantly impact the observed effect on our predictor variables on treatment attendance and Part B eligibility (Salcicioli et al., 2016). This also assessed the robustness of our models.

Chapter 3

Results

Demographic and Descriptive Statistics

Program recorded indicated that participant's IFSP wait time ranged from 8 days to 45 days (M = 24.37, SD = 8.23), and service wait time ranged from 7 days to 132 days (M=42.74, SD=25.36). Most participants received a combination of both telehealth and in-person care (48.65%), or had four services (38.61%), or two service providers (46.69%). After EI services were completed, records indicated that 71.15% of participants were Part B Eligible. For treatment attendance, the mean days of attendance were 47.83 (SD = 22.64) and mean days for amount of treatment planned clinical encounters were 57.37 (SD = 24.05). For treatment attendance, the mean days of attendance were 47.83 (SD = 22.64). Demographic and descriptive statistics can be found in Table 1.

Table 1

Demographic Characteristics and Descriptive Statistics

Characteristics	*M*	*SD*	*f*	%
Age	19.6	6.3	-	-
Gender	-	-		
Male			323	78.97
Female			86	21.03
Race	-	-		
White			173	42.29
Black			110	26.89
Hispanic			69	16.87
Asian/Pacific Islander			57	13.93
Modality	-	-		
In-Person			123	30.07
Telehealth			87	21.27
Combination			199	48.65
Services	3.07	1.9		
1			41	0.10
2			78	19.07
3			116	28.36
4			158	38.63
5			16	00.04
SPP	2.3	0.7		
1			51	12.47
2			191	46.69
3			163	39.85
4			4	0.01
IFSP wait time	23.4	8.2	-	-
Service wait time	42.7	25.36	-	-
Eligibility	-	-		
Yes			291	71.15
No			119	29.10
Treatment planned	57.37	24.1	-	-
Treatment attended	47.08	22.6	-	-

Bivariate Associations and Effect Sizes

Bivariate associations between continuous variables were assessed using Pearson correlation coefficients. Age was positively correlated with SPP, $r(407) = 0.35$, $p < .001$, and negatively correlated with treatment attendance, $r(407) = -0.17$, $p < .001$. Services exhibited positive correlations with SPP, $r(407) = 0.58$, $p < .001$, and treatment planned, $r(407) = 0.37$, $p < .001$, while negatively correlating with Treatment attendance, $r(407) = -0.57$, $p < .05$. SPP showed positive correlations with IFSP wait time, $r(407) = -0.04$, $p < .001$, and treatment planned, $r(407) = 0.11$, $p < .001$. Treatment planned displayed negative correlations with Age, $r(407) = -0.09$, $p < .05$, and Service wait time, $r(407) = -0.08$, $p < .001$, but positive correlations with Services, $r(407) = 0.37$, $p < .001$, and SPP, $r(407) = 0.11$, $p < .001$. Additionally, Treatment attendance correlated negatively with Age, $r(407) = -0.17$, $p < .001$, Services, $r(407) = -0.57$, $p < .05$, and SPP, $r(407) = -0.03$, $p < .001$ (see Table 2).

Table 2

Correlation Coefficients and Effect Sizes for Study Variables

Variable	Age	Services	SPA	IFSP wait time	Service wait time	Treatment planned	Treatment attendance	Eligibility
1. Age	-							
2. Services	-0.02	-						
3. SPP	0.35	0.58**	-					
4. IFSP wait time	0.02	0.01	-0.04	-				
5. Service wait time	0.12*	0.50**	0.35**	-0.03	-			
6. Treatment planned	-0.09*	0.37**	0.11**	-0.08	0.39**	-		
7. Treatment attendance	-0.17**	-0.57*	-0.03	-0.07	-0.09	-0.04	-	
8. Eligibility	-0.62**	-0.21**	0.01	-0.06	-0.26**	0.09	0.18**	-

Note. **p<.001; *p<0.5. Pearson’s correlation coefficients are indicated in variables 1 – 7. Spearman correlations are indicated for variable 8.

The Pearson correlations revealed significant correlations among of the study variables. Age demonstrated a positive correlation with the number of SPP which suggested that older children tend to have more programs attached to their case. Moreover, age also showed a negative correlation with treatment attendance which suggested that older children's families attended treatment for fewer days. Services demonstrated positive correlations with SPP and treatment planned. However, services negatively correlated with treatment attendance. This indicates that more recommended services were associated with more program involvement but lower attendance from the families. Treatment planned demonstrated negative associations with age and service wait time but positive associations with SPP and services. Additionally, treatment attendance negatively correlated with age, services, and SPP. This suggested that older children attended treatment less frequently when more services were attached to their case.

Spearman correlations were used for all of our study's continuous variable associations with Eligibility, a binary variable. Age, $\rho(407) = -0.17$, $p < .001$, Services, $\rho(407) = -0.57$, $p < .05$, and SPA, $\rho(407) = -0.03$, $p < .001$. Additionally, treatment planned showed a negative correlation with Eligibility, $\rho(407) = -0.26$, $p < .001$. No significant correlations were found between Treatment attendance and IFSP wait time, service wait time, or treatment planned (see Table 2). Pearson's chi-squared test was conducted to explore the association between treatment modality and eligibility. This revealed a statistically significant association (χ^2 (2) 14.388, $p < 0.001$) which suggested that eligibility varies significantly across each of the different treatment modalities (i.e., In-person, telehealth, combination).

The Kruskal-Wallis test was employed to examine the potential differences in modality across various levels of in-person, combination, and telehealth for all study variables. Significant differences in levels of modality were observed across most of our study variables. Notably, for age, services, SPA, and service wait time, significant disparities in median values were detected among the modalities (H-Scores ranging from 19.22 to 117.23, all p-values < .05) (see Table 3). Specifically, significant differences were found between In-Person and Telehealth modalities, with Combination modalities sometimes exhibiting intermediate values. However, treatment planned and treatment attendance did not demonstrate statistically significant differences across the modalities, as indicated by non-significant H-Scores (0.90 and 6.92, respectively).

Table 3

Kruskal Wallis Test's Values of Types of Modalities

Variable	Modality	Abs. Diff. in Medians	H-Score
Age	In-Person	1	19.22**
	Combination	0	
	Telehealth	1	
Services	In-Person	1	117.23**
	Combination	2	
	Telehealth	1	
SPA	In-Person	1	53.51**
	Combination	2	
	Telehealth	1	
Treatment Planned	In-Person	0	0.90
	Combination	2	
	Telehealth	2	
Treatment Attendance	In-Person	1	6.92*
	Combination	0	
	Telehealth	1	
IFSP wait time	In-Person	1	2.29
	Combination	0	
	Telehealth	1	
Service wait time	In-Person	1	46.91**
	Combination	0	
	Telehealth	1	

Note. *< 0.05, ** < 0.001, *df* = 2

Negative Binomial Regression

To test for assumptions of linearity of our negative binomial regression model, residual plots and partial residual plots revealed no discernible pattern thereby indicating that the relationships were adequately linear. Residual plots were generated by plotting the residuals against the predicted values from the negative binomial regression model. The analysis of the partial residual plots showed evidence of linear relationships after adjusting for the effects of the other variables.

Our analysis revealed that all predictor variables had low VIF values, ranging from 1.02 to 2.15, well below the commonly accepted threshold of 5 (Imdadullah, et al., 2016; O'brien, 2007; Salmerón, et al, 2020). These findings suggest that multicollinearity is not a significant concern among the predictor variables in our model, indicating that they are relatively independent of each other. While some of our variables demonstrated moderate-sized Pearson correlation coefficients with each other (i.e., Planned Treatment Days and Service Providers), the low VIF values indicate that the impact of multicollinearity on the regression coefficients is minimal.

The dispersion parameter (θ) estimated from the negative binomial regression model was a θ=67.206. This value indicated a significant amount of overdispersion in the data and that the observed variance in treatment attendance exceeded what would be expected under a Poisson distribution (Zhang, 2007). Therefore, accounting for overdispersion with the negative binomial regression model was well supported.

We compared the goodness-of-fit of our negative binomial regression model to Poisson regression model in supplement of a null hypothesis model. Several goodness of fit statistics, Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and a likelihood ratio chi-square test were evaluated. The AIC and BIC values for the negative binomial model were 2838.58 and 2874.71, respectively, whereas the Poisson model's AIC and BIC was 3002.10 and 3034.21 respectively. Additionally, the likelihood ratio chi-square test was a 65.518 (p = < 0.001). This small p-value suggested that the negative binomial regression model provided a significantly better fit to the data compared to the Poisson regression model. Overall, the goodness-of-fit statistics suggested that the negative binomial model better captured the overdispersion present in the data.

The results indicated that telehealth services had a statistically significant positive association with treatment attendance ($\beta = 0.22$, 95% CI [0.16-0.28], $p < 0.001$) with an IRR of 1.25 (95% CI [1.17-1.32]). This indicated that for every one-unit increase in the use of telehealth services, the expected count of treatment attendance increases by a factor of 1.25. As for the IRR, this suggested that families who utilized telehealth services were estimated to have a 25% higher treatment attendance rate compared to those who did not use telehealth services after adjusting for the other variables in the model (See Table 4).

Table 4

Negative Binomial Regression Coefficients and Incidence Rate Ratios Statistics

	Treatment Attendance				
	β	SE	95% CI β	IRR	95% CI IRR
Telehealth	0.22**	0.03	0.16-0.28	1.25**	1.17-1.32
Combination	0.18**	0.03	0.12-0.24	1.20**	1.13-1.27
IFSP wait time	0.01	0.12	-0.23-0.25	1.01	0.80-1.28
Service wait time	-0.05*	0.02	-0.09- -0.01	0.95*	0.91-0.99
SPA	-0.02	0.02	-0.06-0.02	0.98	0.94-1.02
Services	-0.05*	0.01	-0.07- -0.03	0.95*	0.93-0.97
Age	0.01	0.04	-0.07-0.09	1.01	0.93-1.09

Note. **p<.001; *p<.05.

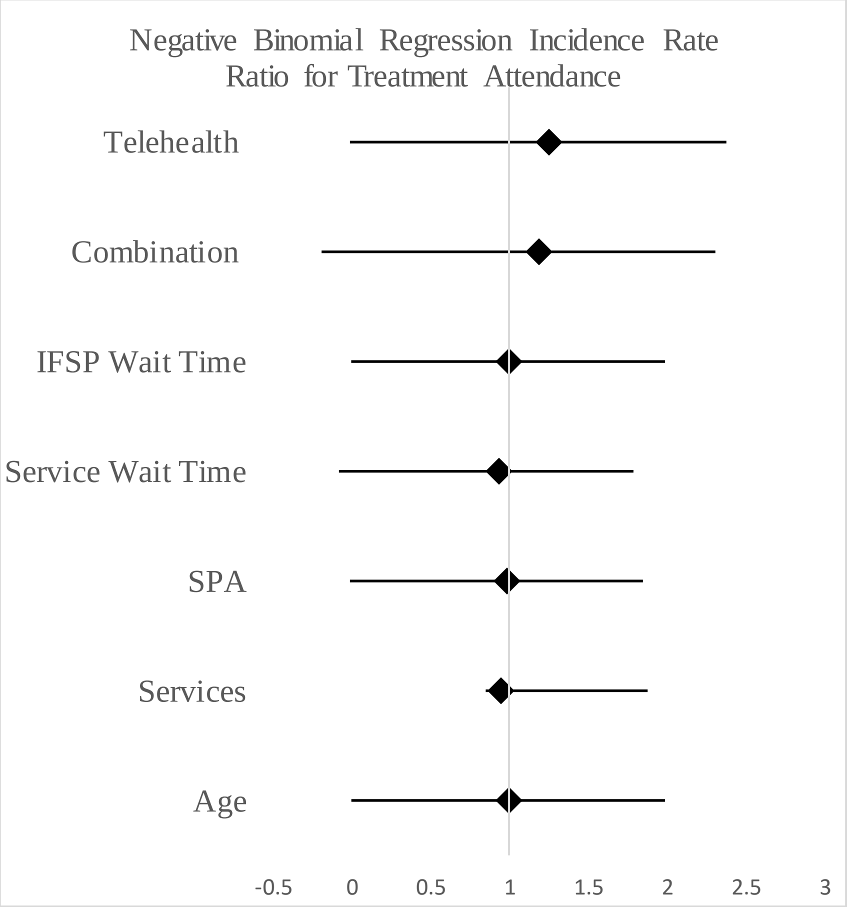
Additionally, the combination of telehealth and in-person services had a statistically significant positive association with treatment attendance ($\beta = 0.18$, 95% CI [0.12-0.24], $p < 0.001$) with an IRR of 1.20 (95% CI [1.13-1.27], $p < 0.001$). This indicated that for every one-unit increase in the use of combined telehealth and in-person services, the expected count of treatment attendance increases by 1.20. The IRR indicated that individuals who utilized combined telehealth and in-person services were estimated to have a 20% higher treatment attendance rate compared to those who did not use combination services, after adjusting for the other variables in the model.

Service wait time also had a statistically significant negative association with treatment attendance ($\beta = -0.05$, 95% CI [-0.09 - -0.01], $p < .001$) with an IRR of 0.95 (95% CI [0.91-0.99], $p < 0.05$). As service wait time increases, treatment attendance tends to decrease. Specifically, for each additional unit increase in service wait time, we expect to see a 5%decrease in treatment attendance. Services had a statistically significant negative association with treatment attendance ($\beta = -0.05$, 95% CI [-0.07 - -0.03], $p < 0.05$) with an IRR of 0.95 (95% CI [0.93-0.97], $p < 0.05$). This coefficient indicated that for every one-unit increase in the number of services provided, the expected count of treatment attendance decreases by a factor of 0.95. The IRR suggested that for each additional service provided, individuals were estimated to have a 5%lower treatment attendance rate, after adjusting for other variables.

IFSP wait time did not reach statistical significance ($\beta = 0.01$, 95% CI [-0.22-0.24], $p = 0.93$) and an IRR of 1.01 (95% CI [0.80-1.28]). These findings suggest that IFSP wait time does not have a statistically significant association with treatment attendance. The IRR being 1 indicated that IFSP wait time does not appear to have a substantive effect on treatment attendance. SPA did not reach statistical significance either (β = -0.02, 95% CI [0.02-0.02], $p = 0.32$) and an IRR of 0.98(95% CI [0.94-1.02]). These findings suggest that the number of SPAs does not have a statistically significant association with treatment attendance. The IRR being 1 indicated that the number of SPAs does not appear to have a substantive effect on treatment attendance. To illustrate the relative importance and impact of each EI predictor variable on treatment attendance, see Figure 2.

Figure 2

Incidence Rate Ratios for Negative Binomial Regression



Note. **p<.001; *p<0.5.

To further assess the robustness of our negative binomial regression model, we conducted a sensitivity analysis by introducing interaction terms between modality and both IFSP wait time and service wait time variables. The aim was to explore potential moderation effects on treatment attendance. We employed the same dummy coding using in our previous model for modality. The resulting model, which included these interaction terms, did not yield statistically significant effects for the interaction terms between modality and IFSP wait time ($\beta = -0.0005$, $p = 0.71$) or service wait time ($\beta = 0.0005$, $p = 0.25$), suggesting that the moderation effects of these variables on the relationship between modality and treatment attendance were not supported. However, a significant effect was observed predictor Services ($\beta = -0.05$, $p < 0.001$) as it remained a significant predictor of treatment attendance. This indicated that the number of services received significantly influenced treatment attendance, independent of the modality and wait times.

The final model equation that showed significance compared to other hypothesized equations is as follows:

$$log: \frac{treatment\ days}{required\ days} = \beta_0 - \beta_1 x\text{Service wait time} + \beta_2 x\text{Services} + \beta_3 x\text{Treatment Modality} + \text{u}$$

As revealed in this equation, the intercept (β_0) signifies the expected log ratio when all predictor variables are zero. The intercept represents the baseline level of treatment attendance when all other factors, such as treatment modality, wait times, and the number of services, are absent or at their reference levels. The coefficients ($\beta_1, \beta_{2,} \beta_3$) indicate the change in the log ratio for a one-unit increase in the corresponding service wait time.

Logistic Regression

For the logistic regression, we conducted a Box-Tidwell test on each predictor variable in our model to ensure that the assumptions of linearity are met, leading to more valid and reliable statistical inference and interpretation before conducting the logistic regression (Pituch, 2015). Most of our model's predictor variables, including IFSP wait time, SPA, services, and modality demonstrated satisfactory adherence to the assumption of linearity in the logistic regression model. The distributions and relationships of these variables did not necessitate transformations to meet the linearity requirements. However, service wait time exhibited departures from linearity in their distributions due to skewness. To ensure conformity with the assumptions of logistic regression, a logarithmic transformation was applied to service wait time (Leydesdorff & Bensman, 2006)

To address the skewed distribution of service wait time and meet the assumption of linearity for logistic regression analysis, a logarithmic transformation was performed on service wait time. This transformation was chosen to stabilize the variance and reduce the skewness observed in the original distribution (Leydesdorff & Bensman, 2006). The resulting transformed variable exhibited a more symmetric distribution and provided a better approximation to the linearity assumption for this regression model. Subsequent analyses were conducted using the transformed variable of service wait time to ensure valid statistical inference. The Holmer-Lemeshow test revealed a non-significant p-value of 0.43 ($\chi 2(8) = 8.06$). Since this p-value was greater than the conventional significance level of 0.05, we fail to reject the null hypothesis (Menard, 2002). Therefore, we do not have sufficient evidence to conclude that there is a significant difference between the observed and expected frequencies of our outcome variable eligibility. In other words, the logistic regression model appears to fit the data adequately according to the Hosmer-Lemeshow test.

A Nagelkerke R-squared statistic was calculated to be 0.187 (*df* =1), indicating that approximately 18.7% of the variance in the outcome variable was accounted for by our logistic regression model. In addition, a McFadden's R^2 yielded a value of 0.10, suggesting that approximately 10 % of the variance in the outcome variable was explained by our model. Taken together, these findings suggest that our logistic regression model modestly explains the variability in the outcome variable.

Telehealth demonstrated a significant positive effect on the likelihood of ineligibility for Part B services ($\beta = 1.19$, SE = 0.34, $p < .001$) (see Table 5).

Table 5

Logistic Regression Analysis of Statistics of Predictors of Ineligibility for Part B Services

	Ineligibility for Part B After EIP Completion					
	β	*SE* β	95% *CI* β	Wald χ^2	*OR*	95% *CI OR*
Telehealth	1.19**	0.34	0.52 -1.86	12.25	3.30*	1.69 – 6.40
Combination	0.93*	0.34	0.26 - 1.60	7.48	2.53*	1.30 - 4.94
IFSP wait time	-0.02	0.01	-0.04 - -0.00	4.00	0.98	0.96 – 1.00
Service wait time	-0.01*	0.01	- 0.03 - 0.01	1.00	0.99*	0.97 - 1.01
SPA	-0.40	0.24	-0.87 - 0.07	2.78	0.67	0.42 – 1.07
Services	-0.29*	0.14	-0.56 - -0.02	4.29	0.75*	0.57 – 0.98
Age	0.01	0.01	-0.01 - 0.03	1.00	1.01	0.99 - 1.03

Note. **p<.001; * p<.05

This indicated that for each unit increase in the Telehealth variable, there was a corresponding increase in the log odds of ineligibility for Part B services compared to those who received on in-person services. The odds ratio for Telehealth was 3.30 (95% CI [1.69 - 6.40]), suggesting that participants who received Telehealth services were 3.30 times more likely to be ineligible for Part B services compared to those who received In-Person services. Combination of Telehealth and In-Person services had a significant positive effect on the likelihood of ineligibility for Part B services (β = 0.93, SE = 0.34, p < .05). This indicated that for each unit increase in the Combination, there was a corresponding increase in the log odds of ineligibility for Part B services. The odds ratio for Combination was 2.53 (95% CI [1.30 – 4.94]), indicating that participants who received a combination of Telehealth and In-Person services were 2.53 times more likely to be ineligible for Part B services compared to those who solely received In-Person services.

Service wait time exhibited a significant negative effect on the likelihood of ineligibility for Part B services (β = -0.01, SE = 0.01, p < .05). This indicated that for each unit increase in service wait time, there was a corresponding decrease in the log odds of ineligibility for Part B services. The odds ratio for service wait time was 0.99 (95% CI [0.97 - 1.01]), indicating that for each additional unit of service wait time, participants' odds of ineligibility decreased by approximately 1.1%. The number of services received revealed a significant negative effect on the likelihood of ineligibility for Part B services (β = -0.29, SE = 0.14, p < .05). This suggested that for each unit increase in Services, there was a corresponding decrease in the log odds of ineligibility for Part B services. The odds ratio for the number of services was 0.75 (95% CI [0.57 -

0.98]), indicating that participants who received more services during EIP were 0.75 times as likely to be ineligible for Part B services compared to those who received fewer services.

Service providers, IFSP wait time, and Age did not emerge as significant predictors of ineligibility for Part B services (all $p > .05$). The beta coefficients for the number of service providers ($\beta = -0.40$), IFSP wait time ($\beta = -0.02$), and age ($\beta = 0.01$) were not statistically significant. Similarly, the corresponding odds ratios for the number of service providers (OR = 0.67, 95% CI [0.42 - 1.07]), IFSP wait time (OR = 0.98, 95% CI [0.96 - 1.00]), and age (OR = 0.99, 95% CI [0.99 - 1.03]) indicated no significant associations with ineligibility for Part B services.

Cross-validation was conducted to assess the performance of the logistic regression model in predicting eligibility for Part B services. The model was subjected to 10-fold cross-validation to evaluate its generalization ability across different subsets of the dataset, a common recommended subjection (Krstajic et al.,2014; Olsen, 2024). The logistic regression model exhibited an average accuracy of approximately 72.8% (M = 0.73, SD = 0.49). This indicates that, on average, the model correctly classified individuals as eligible or ineligible for Part B services about 73% of the time across the 10 folds of cross-validation. Additionally, the Kappa (k) coefficient, measuring agreement beyond chance, was found to be approximately 0.21 (M = 0.21, SD = 0.11), suggesting a fair level of agreement between predicted and actual classes. These findings suggest that the logistic regression model demonstrates moderate predictive performance in determining eligibility for Part B services.

The final model equation that showed significance compared to the null hypothesized equations is as follows:

$$Part\ B\ Ineligibility = \beta_0 - \beta_1 x\text{Service wait time} + \beta_2 x\text{Services} + \beta_3 x\text{treatment modality} + \text{u}$$

As revealed in this equation, the intercept (β_0) signifies the expected regression equation when all predictor variables are zero. The intercept represents the baseline level of Part B Eligibility when all other factors, such as treatment modality, wait times, and the number of services, are absent or at their reference levels. The coefficients (β_1, $\beta_{2,}$ β_3) These coefficients quantify the impact of each independent variable on the log odds of the outcome variable (Part B Ineligibility) in our final logistic regression model. They indicate the direction and magnitude of the effect that changes in each independent variable have on the likelihood of being ineligible for Part B.

Chapter 4

Discussion

Overview of Results and Conclusion

Overview of Results

This research marks preliminary efforts to tackle issues related to coordinating care and engaging families in NJ Early Intervention System (NJEIS). The study focused on examining the factors that could both predict attendance and eligibility for Part B services among families enrolled in NJEIS. In our study, we set out with two hypotheses guiding our exploration. The first hypothesis predicted that extended wait times, more providers attached to a child's case, more service agencies, and the absence of telehealth options would result in lower attendance rates for treatment among families. The second hypothesis suggested that that extended wait times, more providers attached to a child's case, more service agencies, and the absence of telehealth options would predict higher rates of eligibility for Part B services.

One of our most significant results indicated that the type of treatment used plays a role in predicting treatment attendance and eligibility for Part B services. The analysis from the Kruskal Wallis test backs up our regression analysis by showing notable variations between different treatment approaches with a focus on factors influencing attendance. Our regression analysis delved deeper and found that using telehealth options alone or in combination with in-person visits showed positive links to higher attendance rates and greater chances of seeing clinical improvements. This finding corresponds with similar EI research literature exploring EI telehealth options for families in the context of telehealth use in healthcare by offering proof of the benefits of using combined options (Ashburn et al., 2014; Baharav & Reiser, 2010). The importance of the treatment method, as demonstrated in our findings, emphasizes how remote healthcare options can potentially improve participants' involvement and clinical progress through EIP advantages.

Our study showed significant connections between the service wait time and eligibility for Part B benefits. Families who had shorter waiting periods from the start of services were less likely to qualify for Part B services. This highlights the significance of accessing EIPs across NJ to ensure that crucial support services are streamlined to families in a timely manner. This finding corresponds with other EI literature on the clinical significance of reducing service wait times for care (Awad et al., 2019; Bernie et al., 2021; Gordon Lipkin et al., 2016). Our study builds upon this by delving further into specific time points of service delivery, considering that the EIPs may have different service checkpoints before care is commenced. This discovery sheds light on the initial stages of the EIS, where prolonged wait times could have adverse effects on families. Past studies have emphasized the importance of tackling similar obstacles in EI service provision by diminishing wait times and minimizing factors that could disrupt treatment progress (Atmojo et al., 2020; El Sapiets et al., 2021). This finding provides additional evidence to the role of timely services to guarantee accessibility and involvement of families, with crucial resources and assistance.

The number of services allocated for a child's care was found to be a factor in predicting the family's overall attendance and eligibility. In the present study, participants with a higher number of services demonstrated lower attendance rates. This suggested probably difficulties that families may have experienced handling various intervention methods at the same time. Moreover, having more services was closely linked to longer service waiting periods which may have plausibly increased stress for families as they wait for important services to start. The FAAR model supports this idea by suggesting that the number of services recommended to a family may theoretically become a demand for the family to maintain (Carly Albaum et al., 2020; Patterson, 1998). Furthermore, using this theory's lens, services can act as pressures that exhaust a family's assets and hinder their ability to participate fully. Coordinating care across providers might lower the family's chance of making it to all the appointments provided by each service. This trend is highlighted in studies that explore similar challenges faced by families when managing healthcare providers (Moh & Magiati, 2012; Lopez et al., 2019; Srinivasan et al., 2021). This finding highlights the significance of consolidating services under designated providers to reduce the burden on families and improve adherence to treatment plans.

Our study also found that the length of time, specifically from when someone is referred to EI to when they receive their IFSP, did not significantly affect their attendance or eligibility status. This could be because evaluations are typically done promptly from the referral to the IFSP stage. All individuals in our study received their IFSP within the required 45-day timeframe. Additionally, services provided during this part of the EIP process are usually handled by one evaluation team, which might streamline a timelier IFSP document. Each individual intervention service recommended in the IFSP may be spread out among providers and service organizations. Therefore, there might be other elements that could result in delays in communicating with families.

SPP was not found to be an indicator of treatment attendance or a predictor for Part B eligibility despite our hypothetical expectations. It is possible that other factors, like the organization of services or cooperation among EI providers within agencies, could have an impact on shaping child outcomes (Adams et al., 2013; Harbin et al., 2004; Peterson, 1991). However, these specific aspects were not thoroughly investigated in this study. Further research should explore additional details of how service coordination amongst agencies functions to meet the needs of the families in their area. Taken together, these factors may provide the groundwork for gaining a better understanding of the elements that impact children's progress in early intervention programs.

Conclusion

In summary, the key findings in our study provide evidence-supported perspectives on the factors that affect attendance for treatment and qualification for Part B eligibility. These findings highlight the significance of tailoring service delivery methods to family's needs, ensuring the timely availability of services, and ensuring the choice of telehealth options are proposed to families to improve overall treatment engagement with vital support services.

The study offers valuable insight into factors that impact attendance and Part B eligibility, for children enrolled in NJ EIPs. Our analysis highlights the importance of the type of treatment offered, specifically the utilization of telehealth services provided substantial evidence for predicting positive clinical and service outcomes. This broadens the advantages of offering telehealth care options for NJEIP families. Additionally, this study highlights the significance of access to timely services after the initial IFSP, as it was found that shorter service commencement wait times were linked to lower chances of ineligibility for Part B services.

Limitations and Future Direction

Limitations

There are five significant limitations to our research findings. The primary limitation of this study is its generalizability beyond the data collected for a program in New Jersey County. Using patient care data from one program within a geographic area naturally limits how far-reaching the conclusions can be applied to larger populations or other early intervention programs. A systematic review of various EIPs found that there is significant variation in service delivery models used by individual programs, the demographics of the families they serve, and the resources available to them (Tollan et al., 2023). These findings highlight the need for caution when trying to generalize the results of this study to regions with different EIP setups.

One additional constraint is that our research heavily depended on data gathered during typical clinical procedures rather than rigorous research standardization. It is crucial to emphasize that the data used for this study was archival clinical records which were completed by the providers whose main documentation goals were to meet billing documentation standards and document clinical progress. If families failed to attend scheduled appointments for any reason and this information was not properly recorded by in their records, it's possible that some missed appointments with a family may not have been accurately documented over the course of their treatment. This discrepancy could potentially skew the results of our study regarding missed appointments linked to earlier mentioned factors, especially if the actual number of missed appointments by families exceeds what was observed in our research.

The third limitation is that our study did not include well-established possible confounds, like parental stress levels, the extent of a child’s impairment, socioeconomic status, or caregiver satisfaction. For instance, parental satisfaction with care and overall family burden are factors that are present in the EI literature that have been found to contribute to a family's overall burden to managing stressors (Owen, 2020; Ferro et al., 2021; Trentacosta et al., 2018). Furthermore, while there continues to be increasing access to internet services and technology that can facilitate telehealth at home, barriers remain for low-income families to equitably access these resources (Berger et al., 2022; Kryszak et al., 2022). When we couple these concerns with other prominent sociocultural issues, such as language barriers or poor healthcare literacy, telehealth can also equally become a challenge to incorporate rather than an effective tool.

The degree of impairment of the child at the time of IFSP is a crucial confounding variable that was not captured in the present study. Studies have found that children with higher levels of developmental impairments are more likely to receive EIP services, be recommended higher amounts of services, and have been correlated with higher levels of parental stress (Fi et al. 2022; Shenouda et al., 2022). Therefore, families with less impaired children may benefit more from telehealth services or be able to implement service recommendations more easily virtually compared to families with more severely impaired children due to the more effective degree of impairment. That is, it is plausible that in-person care may offer be a more appropriate medium for teaching parents to help their children if the child's impairment is more severe. If this is the case, the FAAR model would support this because tailoring the modality of care by considering the level of severity would account for the risk of services becoming a demand for one family compared to another (Carly Albaum et al., 2020 and Patterson 1998). Therefore, caution should be taken when interpreting the extent to which our results accurately reflect the needs of all families because it does not account for degree of developmental impairment.

The fourth limitation of our study is that service wait time needed a logarithmic transformation to address its skewness and enhance the linearity assumption for logistic regression analysis purposes. Our findings revealed that longer service wait times had an impact on the likelihood of being ineligible for Part B services. However, the way we interpret this impact is based on the transformed variable, which was essential for the analysis to be conducted between service wait time and the outcome variable. Therefore, it's important to understand the extent of this impact considering the logarithmic transformation employed in our analysis. Although this finding still offers valuable insight, further studies are encouraged to explore the existence of the connection between how long a family waits for services and their child's eligibility status.

The fifth significant constraint of our research is the possibility of historical influences that could have affected the outcomes of the study. The research was carried out at the height of the COVID-19 outbreak in New Jersey, spanning from March 2020 to March 2023. Therefore, due to the unprecedented nature of the pandemic, our findings may have been reflective of historical effects, which reflected the state of healthcare provision and EIP services during that time. Statewide measures such as lockdown restrictions and social distancing could have disrupted healthcare services accessibility leading to changes in attendance rates, wait times, and practices of eligibility assessments. During our study's time period, from March 2020 to March 2021, individual EIP families only received telehealth services initially and then were switched back to receiving in-person services afterward.

The limit to telehealth services during the pandemic could explain the observed relationships between treatment modalities and attendance rates. Research have highlighted the challenges for data validity of behavioral health research during COVID-19, especially when considering the increased stress impacts on families and caregivers of children (Alsiri et al., 2021; Mara, 2020; Massazza et al., 2023). In the early stages of the lockdown, other EIP modality options, like combining services and in-person meetings, were unavailable due to suspension during this time frame. This likely will complicate the interpretation of some of the present study's key findings. For example, the telehealth OR of 3.30, which indicates a chance of being ineligible for Part B services in comparison to in-person services, might not accurately represent the usual scenarios in non-pandemic times. This number needs to be interpreted with the understanding for close to a third of the time this study was conducted families could only access telehealth services.

The pandemic might have also impacted how financial and emotional wellness due to possible strain on resources, which was found to have significantly influenced EI family's engagement with care (Mara, 2020). This means that the families who chose to use services during the lockdown period could be quite different in terms of resources or other characteristics compared to those who deemed telehealth insufficient for their family and child's needs. Understanding the challenges presented by the COVID-19 pandemic is essential to interpreting the results of the research and grasping their wider significance in a healthcare environment shaped by its. aftermath.

Future Direction

Future NJEIP studies exploring similar topics to this study would benefit from focusing on conducting multisite studies to gain a better representation of the state's overall reflection upon factors that contribute to attendance and clinical outcomes. This will allow for comparisons across different contexts and improve the applicability of the results. A multisite study examining telehealth EI care for hearing-impaired children found this methodological approach provides comprehensive scientific insight into the benefit of telehealth across programs (Behl et al., 2017). Consequently, by adopting a location approach within the NJEIS, we could gather a wide range of research data to understand how healthcare system factors are impacting families throughout the state. Moreover, studying the factors that affect the variability of programs and how they influence the results of interventions can help us understand why outcomes vary in situations specific to each family. By conducting research and refining our methods to address the issue of generalizability, future efforts progress toward creating interventions that are more widely relevant. In essence, these initiatives aim to improve outcomes for children and families participating in intervention programs outside of New Jersey.

Clinical and Service Delivery Implications

The present study marks an initial effort to understand various predictive issues with family engagement and clinical improvement in the NJEIS, particularly focusing on wait times and telehealth practices and managing healthcare providers' roles in the process. The service provision issues that this study attempted to address are not limited to the state region where it was conducted; rather, they hold promise for guiding research into engagement with EI treatment and clinical outcomes across various regions as well.

Moreover, the study sheds light on how telehealth impacts treatment engagement and carries implications for healthcare for children with developmental concerns. Many studies exploring the impact and popularity of telemedicine in the field of healthcare have shown varying findings and continue to be a significant growing point in EI literature (Ashburn et al., 2016; Cole et al., 2019; Juarez et al., 2018; Yang et al., 2021). While the study's results may not definitively resolve these issues with existing literature data, it does enhance the ability of healthcare professionals to make informed decisions based on data-driven findings specific to the nature of conducting EI clinical care. Thus, this study provides evidence on how EIPs can adjust their service delivery practices to better meet the needs of caregivers and help them understand and adapt to these changes.

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