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Leveraging Predictive Analytics to Improve Placement Stability in U.S. Foster Care Systems

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ABSTRACT : This study examined the role of predictive analytics in improving placement stability in U.S. foster care systems, with specific objectives focused on how predictive risk assessment and machine learning-based decision support reduce placement disruptions. An exploratory research design was adopted to explore existing knowledge on the subject and identify key patterns from prior studies. The study relied on secondary data obtained from published academic journals, peer-reviewed articles, conference papers, and policy reports relating to foster care systems and predictive analytics. Data were analysed using thematic analysis. Findings revealed that: predictive risk assessment improves placement stability by enabling early and more accurate identification of children at risk of placement disruption through behavioural, emotional, and demographic risk profiling; machine learning-based placement decision support reduces placement disruptions by improving placement matching accuracy and enabling data driven decisions that align children with more suitable and stable foster care environments. In conclusion, foster care practice is moving toward a more coordinated and information rich approach, where stability is influenced by the ability to interpret complex data patterns and apply them to real world placement decisions in a more systematic and consistent manner. The study recommended that state child welfare agencies in the United States should integrate structured predictive risk assessment tools into their routine case management systems so that social workers can identify children at high risk of placement disruption earlier and respond with timely support before instability occurs.

KEYWORDS: *Predictive Analytics, Placement Stability, Foster Care System*

I. INTRODUCTION

The foster care system in the United States was established to provide temporary protection and support for children who could no longer remain safely with their biological families because of abuse, neglect, abandonment, or other difficult family conditions. Over the years, the system has faced increasing pressure due to rising numbers of vulnerable children, shortage of foster homes, inadequate funding, and growing concerns about the quality of care provided to children in placement (Elgin, 2018; Lee et al., 2024; Slaugh et al., 2025). One of the most serious challenges within the foster care system has been placement instability, where children experience repeated movement from one foster home or care setting to another (Vreeland et al., 2020). Frequent placement changes often expose children to emotional trauma, poor educational performance, behavioural difficulties, and mental health problems (Clemens et al., 2018). These disruptions may also weaken children's sense of belonging and trust, thereby affecting their long term development and future relationships. As child welfare agencies continue to search for more effective ways of supporting children in care, attention has shifted toward the use of technology and data driven decision making in social services. Predictive analytics has increasingly gained recognition in different sectors because of its ability to identify patterns, forecast outcomes, and support informed decision making (Siebert, 2025). Its growing application in child welfare management has created opportunities for improving service delivery and reducing placement related challenges in foster care systems across the United States (Chor et al., 2025).

Placement stability remains one of the most important indicators of effectiveness within the U.S. foster care system because stable placements contribute greatly to the emotional, educational, and psychological well being of children in care. Children who remain in stable foster homes are more likely to build healthy relationships with caregivers, maintain academic progress, and achieve positive social outcomes (Clemens et al., 2018). In contrast, unstable placements often result in stress, anxiety, behavioural problems, and poor adjustment outcomes among children and adolescents (Vreeland et al., 2020). Child welfare agencies therefore place strong emphasis on reducing unnecessary placement disruptions and improving permanency outcomes for children under their supervision. At the same time, predictive analytics has become highly relevant in today's organizational and administrative environment because institutions increasingly rely on data to improve efficiency, planning, and service delivery (Elgin, 2018). In sectors such as healthcare, finance, education, and social welfare, predictive analytics is used to forecast future events, identify high risk cases, and support better allocation of resources (Chor et al., 2025). Within foster care systems, predictive analytics allows agencies to analyze large volumes of child welfare data to identify children who may be at risk of placement breakdown, emotional distress, or repeated movement across care settings (Ahn et al., 2021). The relevance of predictive analytics has also grown because social service agencies are expected to make faster and more accurate decisions despite limited resources and increasing case complexity. Through the use of predictive models and machine learning tools, caseworkers and administrators are able to make evidence based decisions that improve the quality of care provided to vulnerable children (Trudeau et al., 2023). As public institutions continue to embrace digital transformation and data based management practices, predictive analytics has become an important tool for improving operational outcomes in child welfare systems.

Predictive analytics improves placement stability in foster care systems by helping child welfare agencies identify risk factors associated with placement disruptions before such disruptions occur. Through the analysis of historical and current child welfare data, predictive models can detect patterns relating to age, behavioural conditions, emotional needs, family background, placement history, and caregiver characteristics that may increase the likelihood of placement instability (Vreeland et al., 2020). This allows caseworkers to intervene early by providing additional support services, counselling, or specialized care to children and foster families who may require extra attention. Predictive risk assessment tools also assist agencies in matching children with foster homes that are more compatible with their emotional, behavioural, and developmental needs, thereby reducing the possibility of placement failure (Trudeau et al., 2023). Machine learning based placement decision support systems further improve decision making by examining large amounts of information more accurately and quickly than traditional assessment methods (Chor et al., 2025). These systems help child welfare professionals predict which placement arrangements are most likely to succeed based on previous outcomes and similar case histories. In addition, predictive analytics contributes to better resource allocation because agencies can identify children with the highest level of need and direct support services toward them in a timely manner. This reduces delays in intervention and improves coordination among child welfare professionals. As foster care agencies continue to face increasing demands and limited resources, predictive analytics provides a practical approach for improving placement stability, minimizing repeated placement changes, and promoting better outcomes for children in care.

Children placed in foster care require stable living arrangements that support their emotional growth, educational progress, and psychological development. Foster care agencies are responsible for ensuring that children are placed in safe and supportive homes where they can build trust, maintain consistent relationships, and receive proper care throughout their stay in the system. Placement decisions are supposed to be guided by careful assessments of children's emotional, behavioural, and developmental needs in order to reduce unnecessary movement between foster homes (Stevens et al., 2020). In recent years, the increasing availability of digital technologies and data management systems has provided child welfare agencies with opportunities to improve decision making through predictive analytics. By using historical and real time data, predictive analytics can assist social workers and administrators in identifying children who may be vulnerable to placement disruptions and in selecting placement arrangements that are more suitable for their needs (Ahn et al., 2021). This approach supports timely interventions, informed case management, and improved placement outcomes for children in foster care.

Despite the growing interest in predictive analytics within child welfare systems, placement instability appears to remain a major challenge in many foster care agencies across the United States (Berger & Slack, 2020). Many children continue to experience repeated placement changes due to behavioural difficulties, poor placement matching, emotional challenges, and limited support for foster families (Vreeland et al., 2020). Traditional placement decision making processes often rely heavily on manual assessments and professional judgement, which may not always capture the full range of factors influencing placement outcomes. Although some agencies have started adopting predictive tools and machine learning based systems, their application remains inconsistent and limited across different states and child welfare organizations (Siebert, 2025). In some cases, social workers may lack adequate training or technological support to effectively use predictive systems in placement planning. Existing studies have also shown concerns regarding bias, fairness, and reliability in predictive models used within child welfare settings (Ahn et al., 2021). As a result, many foster care systems continue to struggle with placement disruptions and difficulties in achieving stable care arrangements for vulnerable children.

The persistence of placement instability within foster care systems has serious consequences for children, caregivers, and the wider child welfare system. Children who experience repeated movement between foster homes are more likely to suffer from emotional distress, anxiety, depression, poor academic performance, and behavioural problems (Clemens et al., 2018). Frequent placement disruptions may also weaken children's ability to form lasting relationships and reduce their chances of achieving permanency through reunification or adoption. Foster families and caregivers may experience stress and frustration when placements break down repeatedly, which can discourage continued participation in foster care programmes. In addition, repeated placement changes increase administrative costs and place additional pressure on already stretched child welfare agencies (Elgin, 2018). Failure to effectively apply predictive analytics in placement planning may therefore continue to limit the ability of foster care systems to provide stable and supportive environments for children in care. This situation has created the need for further research on the role of predictive analytics in improving placement stability in U.S. foster care systems (Greenlee & Blaustein, 2026; Chor et al., 2025).

Although studies by Greenlee and Blausetin (2026), Chor et al. (2025), Siebert (2025), Trudeau et al. (2023), Ahn et al. (2021), Stevens et al. (2020), Vreeland et al. (2020), Clemens et al. (2018), Elgin (2018), Hong et al. (2018), and Benesh (2017) have examined predictive analytics, placement instability, permanency outcomes, behavioural risks, and machine learning applications in child welfare systems, existing literature remains fragmented and largely focused on specific predictive models, disability categories, educational outcomes, fairness concerns, or localized state datasets. Most previous studies emphasized statistical performance and predictive accuracy without providing a broad exploratory understanding of how predictive risk assessment and machine learning-based decision support collectively improve placement stability across U.S. foster care systems. In addition, limited attention has been given to synthesizing evidence on the practical role of predictive analytics in reducing placement disruptions and strengthening placement decision making within child welfare agencies. Thus, the main objective of this study is to examine the role of predictive analytics in improving on placement stability in U.S. foster care systems. The study addressed the following research questions:

i. How does predictive risk assessment influence placement stability in U.S. foster care systems?

ii. How does machine learning-based placement decision support reduce placement disruptions in U.S. foster care systems?

II. LITERATURE REVIEW

2.0 Conceptual Review

2.0.1 Predictive analytics

Predictive analytics refers to the use of data, statistical methods, and computational techniques to make informed forecasts about future events based on existing patterns (Kumar & Garg, 2018). It involves examining historical and current data to identify trends that can help anticipate likely outcomes in different situations. In simple terms, it is a way of using past information to estimate what may happen next (McCarthy et al., 2022). It is widely used in many fields such as healthcare, business, education, and social services where decision making benefits from forward looking information. Predictive analytics can also be described as a process that turns raw data into useful forecasts that support planning and decision making (Siebert, 2025). It relies on the idea that patterns found in earlier data often repeat or influence future events. This makes it possible to estimate risks, behaviours, or outcomes before they actually occur. In many cases, it helps organizations act early rather than waiting for problems to happen.

Predictive analytics is a tool that combines technology and data interpretation to support better judgment (Abdurahman, 2021). It does not guarantee exact outcomes but provides probabilities that guide decisions. By identifying possible future scenarios, it helps reduce uncertainty and improves preparedness in different systems where timing and accuracy are important. Predictive analytics can also be seen as a structured way of examining information to support anticipation of future conditions. It focuses on recognizing relationships within data and using those relationships to project what may happen later. This approach is especially valuable in environments where large amounts of information must be processed quickly to support decision making (Kumar & Garg, 2018). In all, predictive analytics is a data driven approach that supports forecasting, planning, and decision support by using existing information to estimate future outcomes in a structured and systematic way.

2.0.2 Placement stability

Placement stability refers to the consistency and continuity of care arrangements for individuals, especially children placed in foster care or similar support systems (Carnochan et al., 2013). It describes a situation where a child remains in the same foster home or care setting for a sustained period without frequent or unnecessary movement. In simple terms, it reflects how steady and uninterrupted a child's living arrangement is while under care (Rubin et al., 2007). Placement stability can also be described as the condition where changes in care environments are minimal, allowing individuals to remain in a supportive and familiar setting. It is often associated with consistency in caregiving relationships, daily routines, and emotional support systems. When stability is present, children are less likely to experience repeated disruptions that affect their adjustment and well being. Placement stability is also a measure of how well a care system is able to maintain suitable matches between children and their foster environments over time (Bernedo et al., 2016). It reflects how successfully placements meet the needs of children without requiring frequent relocation. A stable placement indicates that the child's emotional, behavioural, and developmental needs are being adequately supported within one consistent environment (Carnochan et al., 2013). Placement stability can also be described as the absence of repeated placement breakdowns within a care system. It focuses on continuity in living arrangements and the avoidance of unnecessary transitions between different homes or institutions. Stability in placement is often associated with better adjustment and stronger relationships between children and caregivers.

2.1 Theoretical Framework

This study was underpinned by Diffusion of Innovations Theory which was developed by Everett Rogers in 1962 (Nworie & Okafor, 2023). The theory emerged from studies on how new ideas and technologies spread within social systems over time. Rogers et al. (2014) built the theory by drawing from earlier research in sociology, communication, and rural sociology to explain why some innovations are quickly accepted while others are resisted or slowly adopted. Over time, the theory has been widely applied in fields such as education, health, business, and public administration to explain how new practices and technologies move from introduction to widespread use within different groups and organizations.

The theory explains that the adoption of an innovation follows a gradual process influenced by communication channels, time, and the social system in which it is introduced (Wani & Ali, 2015). It proposes that individuals or organizations move through stages which include awareness of the innovation, interest in it, evaluation of its usefulness, trial use, and eventual adoption. It also highlights that people adopt innovations at different rates and are often grouped into categories such as early adopters, early majority, late majority, and laggards. The theory further explains that the perceived advantages of an innovation, its compatibility with existing practices, its complexity, and its observable benefits all influence how quickly it is accepted and used (Nworie & Okafor, 2023).

In relation to this study, Diffusion of Innovations Theory is relevant because predictive analytics represents a new technological approach being introduced into U.S. foster care systems. Child welfare agencies vary in how quickly they accept and integrate such tools into placement decision making processes. The theory helps explain the factors that influence whether predictive analytics is adopted by social workers and administrators, including their perception of its usefulness in improving placement stability and reducing disruptions. It also supports understanding of how machine learning based systems gradually become part of routine child welfare practice as agencies move from traditional decision making methods toward data driven approaches.

2.2 Synthesis of Existing Empirical Studies

A synthesis of existing empirical literature shows that predictive analytics in foster care systems has been examined from different but related perspectives, particularly around risk identification, placement decision support, and outcome prediction. Greenlee and Blaustein (2026) demonstrated that placement instability is not uniform across groups, as disability type, especially emotional disabilities, significantly increases placement disruptions, while Ahn et al. (2021) similarly showed that predictive models can identify youths at risk of leaving care without permanency, although concerns about fairness and error rates remain. Vreeland et al. (2020) also confirmed that behavioural and emotional indicators strongly predict placement instability, reinforcing the importance of early risk identification. These studies collectively show that predictive risk assessment is effective in identifying vulnerable children, but they also reveal that existing models often focus on isolated risk factors rather than integrating broader system level stability outcomes.

Further evidence from Chor et al. (2025), Trudeau et al. (2023), and Elgin (2018) highlights the growing use of machine learning based decision support systems in improving placement related decisions. Chor et al. (2025) found that machine learning models such as random forest significantly outperform traditional methods in predicting placement service needs, while Trudeau et al. (2023) reported that algorithmic systems can recommend more suitable placement types with strong predictive accuracy. Elgin (2018) also showed that boosted tree models can achieve very high accuracy in predicting permanency outcomes, supporting the efficiency of predictive modelling in child welfare decision making. However, these studies mainly emphasize predictive accuracy and operational performance, with less attention to how these tools directly contribute to sustained placement stability over time.

In contrast, Stevens et al. (2020) and Clemens et al. (2018) focus more on assessment processes and educational outcomes linked to placement changes. Stevens et al. (2020) found that predictive indicators can improve home study assessments and reduce subjectivity in placement decisions, while Clemens et al. (2018) highlighted how combined placement and school instability negatively affects academic progress. These studies suggest that stability should be viewed beyond placement alone, yet they do not fully integrate predictive analytics as a continuous system for managing stability outcomes. Similarly, Benesh (2017) emphasizes limitations in predicting changes in care levels, showing that some models perform only moderately and struggle with dynamic placement changes, which raises concerns about reliability in real world application.

Finally, Siebert (2025) and Hong et al. (2018) provide a broader critical perspective by questioning the ethical and structural limitations of predictive systems. Siebert (2025) warns that predictive analytics may reinforce bias and suggests system level alternatives such as simulation models, while Hong et al. (2018) shows that similar predictive approaches used in homelessness systems identify risk patterns but still struggle with long term stability outcomes. Across all studies, there is agreement that predictive analytics is valuable for identifying risk and supporting decisions, but there is still limited integration of these tools into a unified approach that directly explains how predictive risk assessment and machine learning together improve long term placement stability in foster care systems.

III. METHODOLOGY

This study adopted an exploratory research design to examine the role of predictive analytics in improving placement stability in U.S. foster care systems. The exploratory design was considered appropriate because the study seeks to gain deeper understanding of an emerging area where predictive analytics is increasingly being applied to child welfare decision making, but where evidence remains scattered and still developing (Nworie et al., 2026). Exploratory research allows the researcher to examine concepts, identify patterns, and build insights from existing knowledge without manipulating variables or testing controlled hypotheses. In this context, it provides a flexible framework for exploring how predictive risk assessment and machine learning-based decision support contribute to placement stability in foster care systems.

The study relied exclusively on secondary data for data collection. The data were obtained from published academic journals, peer-reviewed articles, conference papers, policy reports, and relevant institutional publications focusing on foster care systems, child welfare outcomes, and predictive analytics applications. These sources were selected based on their relevance to the research objectives, credibility, and contribution to understanding placement stability and data- driven decision-making in child welfare. Studies from different contexts, particularly those focusing on the United States foster care system, were prioritized in order to ensure contextual alignment with the focus of the research. The use of secondary data allowed the researcher to draw from a wide range of empirical findings and theoretical perspectives without the limitations associated with primary data collection such as time constraints, access to participants, and ethical approval processes involving vulnerable populations.

Data analysis was conducted using thematic analysis. This method was selected because it enables the systematic identification, organization, and interpretation of recurring patterns or themes within qualitative data. The process involved a careful review of the collected literature to identify key ideas relating to predictive risk assessment, machine learning-based decision systems, and placement stability outcomes. The analysis began with familiarization of the data through repeated reading of selected studies, followed by the generation of initial codes based on relevant statements and findings. These codes were then grouped into broader themes that reflected the research questions of the study.

The themes were further reviewed and refined to ensure consistency and alignment with the objectives of the research. Key themes that emerged included early identification of placement risks, improved matching of children to foster homes, reduction of placement disruptions through predictive modelling, and enhanced decision-making efficiency in child welfare systems. These themes were then interpreted in relation to existing literature to draw meaningful conclusions about the role of predictive analytics in foster care placement stability.

IV. DATA ANALYSIS

a. Analysis of Research Question I

i. How does predictive risk assessment influence placement stability in U.S. foster care systems?

The empirical findings collectively show that predictive risk assessment plays a central role in identifying early indicators of placement instability in foster care systems. Studies such as Vreeland et al. (2020) and Ahn et al. (2021) demonstrate that risk assessment tools using behavioural, emotional, and demographic data can effectively predict children who are more likely to experience placement disruptions. Vreeland et al. (2020) found that internalising and externalising behaviours, emotional dysregulation, and older age significantly increase the likelihood of placement breakdown, while Ahn et al. (2021) similarly showed that algorithmic models can identify youths at risk of exiting care without permanency years in advance. These findings suggest that predictive risk assessment improves placement stability by enabling early identification of high-risk cases before disruptions occur.

Further evidence from Greenlee and Blaustein (2026) and Benesh (2017) highlights that risk is not evenly distributed among foster children. Greenlee and Blaustein (2026) showed that emotional disabilities and demographic factors such as age and race significantly shape placement instability patterns, while Benesh (2017) found that child, caregiver, and caseworker variables interact to influence placement changes over time. This suggests that predictive risk assessment contributes to stability by capturing complex and multi layered risk profiles that traditional assessment methods often overlook. However, Benesh (2017) also noted that predictive performance is sometimes moderate, indicating limitations in fully capturing dynamic placement changes. Chor et al. (2025), Elgin (2018), and Stevens et al. (2020) further reinforce that predictive risk assessment improves decision making efficiency in child welfare systems. Chor et al. (2025) found that machine learning models identify youths in need of placement stabilisation services with significantly higher accuracy than traditional methods, while Elgin (2018) reported that predictive models achieve very high accuracy in forecasting permanency outcomes. Stevens et al. (2020) added that predictive indicators improve consistency in assessment processes and reduce subjectivity in placement decisions. Together, these findings suggest that predictive risk assessment strengthens placement stability by improving accuracy, consistency, and early intervention in placement decision processes. Finally, Siebert (2025) introduces a critical perspective, noting that while predictive systems can identify risk, they may also reinforce bias and provide misleading certainty. This indicates that although predictive risk assessment improves stability outcomes, its influence is not without limitations and must be carefully managed to avoid ethical and systemic challenges.

***Major finding for Research Question I*:** Predictive risk assessment improves placement stability by enabling early and more accurate identification of children at risk of placement disruption through behavioural, emotional, and demographic risk profiling.

b. Analysis of Research Question II

ii. How does machine learning-based placement decision support reduce placement disruptions in U.S. foster care systems?

The empirical evidence shows that machine learning-based decision support systems significantly reduce placement disruptions by improving the accuracy and quality of placement decisions. Chor et al. (2025) found that random forest models outperform traditional regression approaches in identifying youths who require placement stabilisation, achieving much higher precision in targeting high need cases. Similarly, Trudeau et al. (2023) demonstrated that machine learning models can recommend more suitable placement types, with approximately 80 percent of youths achieving better outcomes when placed according to model recommendations. These findings indicate that machine learning improves placement matching, which directly reduces the likelihood of placement breakdown. Elgin (2018) and Ahn et al. (2021) further support the effectiveness of machine learning systems in improving placement outcomes. Elgin (2018) showed that boosted tree models can predict permanency outcomes with very high accuracy, suggesting that decision support tools can guide more stable long term placements. Ahn et al. (2021) also found that gradient boosting and random forest models can detect youths at risk of non permanency, allowing for targeted interventions that reduce future placement disruptions. However, Ahn et al. (2021) also reported error rates, indicating that while machine learning improves decision making, it is not fully error free. Vreeland et al. (2020) and Stevens et al. (2020) highlight how machine learning supports stability by improving operational decisions. Vreeland et al. (2020) found that predictive models based on routine child welfare data can identify children at risk of placement disruption, while Stevens et al. (2020) showed that structured predictive indicators reduce subjectivity in home study assessments and improve efficiency. These improvements in assessment and placement processes contribute to fewer disruptions and better continuity in care. However, Siebert (2025) cautions that machine learning systems may introduce ethical concerns and reinforce bias if not properly managed. This suggests that while machine learning-based decision support reduces placement disruptions, its effectiveness depends on fairness, transparency, and proper system design.

Major finding for Research Question II: Machine learning-based placement decision support reduces placement disruptions by improving placement matching accuracy and enabling data driven decisions that align children with more suitable and stable foster care environments.

V. CONCLUSION AND RECOMMENDATION

The findings point to a shift in how foster care systems understand and manage placement decisions, especially in relation to improving continuity of care for children. The growing use of structured data to identify children at risk of disruption reflects a move toward more anticipatory forms of decision making within child welfare practice. This means that information about behavioural patterns, emotional needs, and background characteristics is increasingly shaping how professionals interpret risk and stability, rather than relying mainly on observation or experience alone. As a result, placement planning becomes more informed by consistent patterns across cases, which helps reduce uncertainty in decision processes. At the same time, the use of machine learning in placement matching reflects a broader transformation in how suitability between children and foster homes is determined, as decisions are now influenced by computational analysis of large datasets that reveal patterns not easily detected through manual assessment. This changes the traditional approach to placement, where professional judgement alone was central, by introducing a more structured and evidence based layer to decision making. It also highlights how foster care systems are gradually aligning operational practices with data driven approaches that emphasize accuracy, consistency, and long term stability outcomes. In addition, the integration of predictive and machine learning tools suggests a growing interdependence between human decision makers and technological systems in child welfare administration, where both work together to shape placement outcomes. This reflects a broader evolution in service delivery models within social systems, where technology increasingly supports the identification of suitable care arrangements and reduces reliance on reactive responses to placement breakdowns. In all, the results indicate that foster care practice is moving toward a more coordinated and information rich approach, where stability is influenced by the ability to interpret complex

data patterns and apply them to real world placement decisions in a more systematic and consistent manner.
The study recommended:

1. State child welfare agencies in the United States should integrate structured predictive risk assessment tools into their routine case management systems so that social workers can identify children at high risk of placement disruption earlier and respond with timely support before instability occurs.
2. Federal and state foster care authorities should adopt machine learning based placement decision support systems within their placement matching processes to improve the accuracy of child–home matching decisions and reduce avoidable placement disruptions across foster care networks.

a. Contribution to Knowledge

This study responds to the gaps identified in the literature by bringing together the fragmented evidence from studies such as Greenlee and Blaustein (2026), Chor et al. (2025), Siebert (2025), Trudeau et al. (2023), Ahn et al. (2021), Stevens et al. (2020), Vreeland et al. (2020), Clemens et al. (2018), Elgin (2018), Hong et al. (2018), and Benesh (2017), which have each examined predictive analytics, placement instability, permanency outcomes, behavioural risks, and machine learning applications in child welfare systems from different angles. Unlike previous works that concentrated on specific models, isolated outcomes, disability categories, fairness issues, or single-state datasets, this study contributes by providing a broader exploratory understanding of how predictive risk assessment and machine learning-based decision support jointly influence placement stability in U.S. foster care systems. It moves beyond focusing only on predictive accuracy or technical performance by examining how these tools are practically applied to reduce placement disruptions and support better placement decisions within child welfare agencies. In doing so, the study offers a more integrated perspective that links predictive analytics directly to placement stability outcomes, thereby addressing the lack of synthesis in existing research and strengthening understanding of how data driven approaches can be used more effectively in foster care practice.

b. Limitations of the Study and Suggestion for Further Studies

This study is based only on secondary data collected from journals, articles, and reports, so it does not include direct information from children, foster parents, or social workers in the field. Because of this, the findings depend on what other researchers have already published, which may not fully reflect current real life situations in all foster care systems. The study also does not use statistical testing since it relies on thematic analysis, so the results are more descriptive than numerical. Differences in data sources and methods across studies may also affect how consistent the findings are. Future studies should collect primary data directly from child welfare workers, foster parents, and children in care to get a clearer understanding of how predictive analytics works in real practice. Researchers can also use surveys or interviews to gather firsthand experiences about placement decisions and stability. There is also need for studies that use statistical methods to test the strength of predictive models in improving placement outcomes. Comparing different states or countries could also help to show how predictive analytics performs in different child welfare systems. More research should also focus on ethical concerns and fairness in using these technologies.

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