Journal of Open Innovation: Technology, Market, and Complexity 9 (2023) 100157

Contents lists available at ScienceDirect

Journal of Open Innovation: Technology, Market, and Complexity

journal homepage: www.sciencedirect.com/journal/journal-of-open-innovation-technology-market-and-complexity

Towards AI-governance in psychosocial care: A systematic literature review analysis

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ARTICLE INFO

Keywords:
Resilience
Wellbeing
Artificial Intelligence
AI-governance
Public services

ABSTRACT

With increased digitalization and e-government services, Artificial Intelligence (AI) gained momentum. This paper focuses on AI-governance in Child Social Care field, exploring how aspects of individual, family/community factors are embedded in organizational level, especially when dealing with children resilience and wellbeing. A three-level based review has been conducted. In the first part we explored the interlink between individual factors associated to either resilience or wellbeing are connected to community and governance level where a new conceptual model is provided. In the second phase, we conducted an in-depth systematic literature review using PRISMA review protocol where new categorizations of identified literature with respect to individual, family and community levels in child social care field were suggested, while in the third phase, a review of relevant AI-initiatives in Europe and USA was performed. Finally, a comprehensive discussion of the literature review outcomes was carried out and a new updated conceptual model was provided.

1. Introduction

With the recent development in the field of computer vision, natural language processing, machine learning, recommender systems and algorithms as wide, Artificial Intelligence (AI) has gone from science fiction to reality, as exemplified by striking innovations such as driverless car, chatbots, computer programs becoming new world champions in various game competitions, among others. Fueled by the internet technology, a huge amount of data raised by mobile apps, home appliance, and IoT sensors enabled AI systems to generate more sophisticated insights, offering more targeted products and services to consumers. This created new socio-economic contexts spanning almost every walk of life from manufacturing, tourism and entailment industries to labor market and social policy. In this context, AI has been like a flexible go-to tool for service innovations with techniques that accommodate various industry sectors (Stone et al., 2016), which generated new added-values that contributed to national / regional economic growth. Google's CEO Sundar Pichai views AI as even more important than the greatest technological advances of mankind, such as electricity or fire (Clifford, 2018). Nevertheless, it is also well acknowledged that the penetration of AI in public and administration sector is much slower than other sectors (e.g., manufacturing, health or entertainment industries), despite the growing adoption of e-government infrastructures, which convey large amount of data and personalization services, for task management and case handling (Zheng et al., 2018; Wirtz et al., 2022) as well as the increasing pressure from regulators for evidence-based policy making. Reasons for such underperformances are various, some of which lie in the far-reaching success of AI applications, which created legal and social challenges that have to do with data accessibility, integrity, privacy, safety, algorithmic bias, explainabiliy of outcomes and transparency. This ultimately made AI governance rather very challenging (Przeganlinska, 2019; Wirtz et al., 2022). Other reasons are rooted back to the fact that the adoption and diffusion of technologies take substantially longer to change organizational performance and legal / cultural issues (Brynjolfsson and Mitchell, 2017; Polikoff and Spinak (2021)). Indeed, this is reflected in empirical study of (Kavanagh et al., 2021), which revealed that millennial Americans are not living in a time of particularly rapid social change when compared to 1900–1950 period, which

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https://doi.org/10.1016/j.joitmc.2023.100157
Received 13 July 2023; Received in revised form 8 September 2023; Accepted 15 October 2023
Available online 21 October 2023

refutes the hypothesis that significant variation in social change occurs in long wave-like cycles. This, for instance, led Fursov and Linton (2022) to suggest integrating product and user innovation paradigms into the Producer-User-Social Innovation model to explain the process of social innovation.

As a consequence, Children Social Care (CSC) governance is one of the public administrations, which is still falling well behind in terms of reliance on AI technology. Concerns about the possible impacts of the growing use of machine learning (ML) in CSC and the potential amplification of the induced systemic bias and discrimination on individuals, families, and communities are legitimately voiced by policy makers (Saxena et al., 2020) to highlight the risk of algorithmic bias with catastrophic consequences when frontline workers engage with families and children. The high impact of CSC governance played a braking role in the emergence of AI-based CSC governance. For instance, a WHO report pointed out that child maltreatment is a major public problem that affects at least 55 million children in the WHO European Region alone (World Health Organization, 2018) so that the impact of a single abuse or a neglect in childhood is detrimental to physical, psychological and reproductive health throughout the life-course. Furthermore, the acknowledged failure rate in AI projects is relatively high. A recent WSJ report indicates that even in industry sector, which exhibits an exponential growth of AI applications, only 53% of AI proof-of-concept projects managed to pass to a production phase (McCormick, 2020). In governance field, the use of AI can potentially exacerbate issues around service delivery, ethics and privacy if not implemented thoughtfully and strategically.

Despite the above legitimate counter-supporting arguments, there is also a growing motivation and pressure to adopt AI-based governance in CSC, especially driven by the relatively high success of AI applications in supporting decision-making in public management with regards to improving the efficiency of internal processes, services, and interaction with citizens (Valle-Cruz et al., 2019). Besides, both national and regional regulators as well as medium-term plans push towards AI-governance in all sectors of activities to accommodate the high diffusion of AI technologies in the society (Sharma et al., 2020). This is further fueled by the adoption by public administrations of powerful e-government tools and e-infrastructures that enable big-data processing and integration of external services, which expect to increase administrative efficiency and cost. In terms of stakeholder benefit, the introduction of AI-based tools in CSC-governance expects to benefit practitioners, parents, children and regulator communities. Practitioners can exploit the advanced risk analysis AI-based tools as well as visualization toolkit to fast explore the various intervention-based initiatives that present high likelihood of success given the child profile and past experiences. Conversational agents can offer substantial help to practitioners by automatically directing some user queries to right services, especially in case of lack of human resources. Similarly, AI-based tools can lead to higher satisfaction of parent community by acknowledging the advanced risk assessment tools employed, visualizing the various hypotheses in a way that ease the understanding of the agency decision-making process as well as recognizing the reduction of administrative burdens created by AI-tools. Besides, AI-based recommender-systems can intuitively empower children community to increase their learning and strengthen their resilience ability. Finally, advanced machine learning and artificial intelligence tools enable governmental agencies and policy makers to profile citizens and provide personalized treatments to parents and children, while optimizing their resources and advance towards evidence-based policing. On the other hand, in CSC field, with the digitalization of the society, new types of children development problems emerged, pushing parents and educators to often solicit help from child welfare services and child psychiatry units. In the long run, this trend expects to make the system burnout and eventually delay the treatment for the children who are in urgent needs for professional interventions. The cross-sector collaboration between all these services not only gives a comprehensive intervention in supporting children's resilience but also provides a decision-support in policy making related to children's well-being. Therefore, the contribution of AI technology can intuitively be of paramount importance in this regard.

The literature of AI-governance in CSC is still in its infancy driven by the scarcity of the applications of AI in public management and multiplicity of guidelines, which are sometimes conflicting, as pointed out in several review and recent studies, e.g., Wirtz et al. (2019); Wirtz et al. (2020); Wirtz et al., 2022; Trudeau et al. (2023); Zheng et al. (2018). For instance, the well-respected AlgorithmWatch foundation (AlgorithmWatch, 2022) identified more than 170 AI guidelines in various stages of development as part of its AI Ethics Guidelines Global Inventory. A key pillar in the development of such policy guidelines in CSC field lies in the specific characteristic of child-users community, often considered as a vulnerable group, which requires special attention to develop their skills in a way that enhances their resilience and wellbeing. It is therefore debatable to which extent this vulnerable group will be involved in the development of the AI-based CSC governance framework. We distinguish the *inclusiveness* trend that advocates an increased horizontal coordination and active engagement with all stakeholder groups in the decision-making process (Wirtz et al., 2022; Sigfrids et al., 2022). While another trend supports a prudent attitude and a relaxation of the *inclusiveness* criteria to ensure timely and effective decisions (Sigfrids et al., 2023). The boundary of the AI-governance has also received different attentions, depending on the extent of the use of AI-tools in the actual governance where a pure decision-aid trend, leaving the user free to complain with the AI-based recommendation or not, and a more vertical integration of AI in the decision-process (see, e.g., discussions in Dafoe, 2018). There are also antagonistic views in terms of approach employed where we distinguish evidence-based management and performance-based management (Heinrich, 2007). Several CSC applications worldwide have also shaped the discussion on the impact of algorithmic bias in the CSC governance. For instance, racially biased algorithms are exhibited in the COMPAS profiling system (Washington, 2018), as a result of the use of historical crime data generated within racially policing to build such systems. The use of AI-predictive or risk assessment for profiling is found to generate significant legal and ethical concerns when treating people differently on the basis of possibilities or calculated futures, not actualities, which violates the fourth amendment prohibiting unreasonable searches and seizures according to (Slobogin, 2008). In overall, although there is an intuitive ground for introducing advanced AI tools in welfare system to enhance citizen's participation, handle the growing sources of big-data entities, enhance risk assessment tools and further improves system security against fraud and misuse of resources, it bears several inherent challenges linked to ethics and governance paradigms, especially with regard to vulnerable groups like children and minority groups.

This motivates the current work which aims to review existing work in a way that uncovers useful insights and triggers new conceptual frameworks for promoting AI-based CSC governance using a systematic literature review-based approach.

For this purpose, a three-stages strategy has been devised in order to maximize the effect of the systematic literature review. First, the cornerstone idea of this study is to explicitly account for the two already mentioned key concepts that impact the mechanism of any CSC governance: child resilience and wellbeing. We therefore initially study the relationship of these two concepts with AI in a way that enhances our understanding of these concepts in the context of an AI-based governance. The output of this preliminary analysis will therefore be used in our systematic review literature through a more concise selection of keywords and data sources. Strictly speaking, several survey papers have been published in the field of child resilience and/or child wellbeing (Linnenluecke, 2017; Pollard and Lee, 2003). Nevertheless, the connection with governance is not strictly emphasized. On the other hand, theoretical and algorithmic approaches using machine learning and big data analytics for predicting child abuse for instance have been promoted in both computer science and social science forums (Gillingham, 2017, 2019a) This provides a sound basis for seeking to reconcile various pieces of evidence that emerged at distinct communities in a way to lie down the foundation for AI-based CSC governance that enhances both child resilience and wellbeing. In the second phase, the output of the first phase will be employed to select appropriate keywords, timeline and resources that will be employed in the systematic literature search using PRISMA protocol (Moher et al., 2009) as well as to guide the subsequent categorization task. In the third phase, we will focus on application parts using potential outcomes from this systematic search complemented by a selected search from more specialized sources (e.g., EU project database). In overall, this paper aims to bridge the gap in the field of CSC-AI-based governance, while attempting to answer the following three research questions that correspond to each phase of the aforementioned three-stage strategy:

Q1. : *What are the specificities of child resilience and child wellbeing and how does this impact CSC governance in public management community?*

Q2. : *What are the scope and the main ingredients for application of AI technology in CSC governance and its potential to reinforce child resilience and wellbeing from literature?*

Q3. : *What is the state of CSC AI-governance in practice and its prospect?*

Fig. 1 provides a high level description of the method employed in this paper and the interlink between the three research questions.

The above research questions implicitly scrutinize the barriers for the emergence of efficient AI-governance in child welfare sector. A light review, in the sense that we restrict the literature search to public management forums, is carried out to answer *Q1*, while a systematic review-based approach using PRISMA protocol is conducted to answer *Q2* benefiting from input from handling of *Q1*. To answer *Q3*, we use both the outcome of the systematic literature search where CSC applications are mentioned and the scrutinizing of publicly available CSC project databases at national and EU levels.

This research yields important theoretical and practical implications. Theoretically, our review provides new insights on different characteristics of barriers and governance strategies induced by involving AI-based technology to enforce child resilience and child wellbeing, and, thus, generating a new understanding of the concept of CSC AI-based governance. In practice, this provides a timely reminder for politicians, public managers, and government administrators to take a transformative leadership in child welfare sector and enable them to manage AI-based innovation in a more effective and proactive manner in the digital era governance.

This article is organized as follows. Section 2 provides relevant background to comprehend the concepts of child resilience and wellbeing as well as their potential link to AI governance. This background will be employed in subsequent analysis and systematic review task, while tackling research question *Q1*. Section 3 details the systematic review-based approach where we describe the eligibility criteria, search strategies, and study design as part of research question *Q2* handling. Section 4 presents the results of the systematic review and draws on potential answers to both research questions *Q2* and *Q3*. Finally, in Section 5, we discuss the findings from public management perspective, draw conclusions and develop a future research agenda on AI-based governance in CSC sector.

2. Resilience and wellbeing

Resilience is described as opposite to vulnerability or, equivalently, the capacity to 'bounce back' from adverse experiences and achieve positive development outcomes despite adversity (Hildon et al., 2008). Wellbeing is the state of being comfortable, healthy or happy. This section provides basic background underpinning the concepts of resilience and wellbeing at individual and community level as well as at governance level with the potential contribution of AI-based governance.

2.1. Resilience and wellbeing at individual level

At individual level, children with higher resiliency are more likely to thrive in learning and less likely to suffer from social or psychological health problems (Benard, 2004). Resilience and wellbeing are intuitively interlinked in the sense that being resilient helps to promote social and emotional wellbeing. Both resiliency and wellbeing are dependent upon internal factors (e.g., personality traits, temperament, chronic illness, intelligence) and external factors (e.g., family conflict, parental education, economical stress, friends' circle, school). Social psychological theory (Bonanno et al., 2015) views resilience as the product of two opposing forces in individual's life: risk factors that act as barriers for achieving wellbeing goals and protective factors that increase resistance to risk factors. Other researchers use the concept of ecological model to

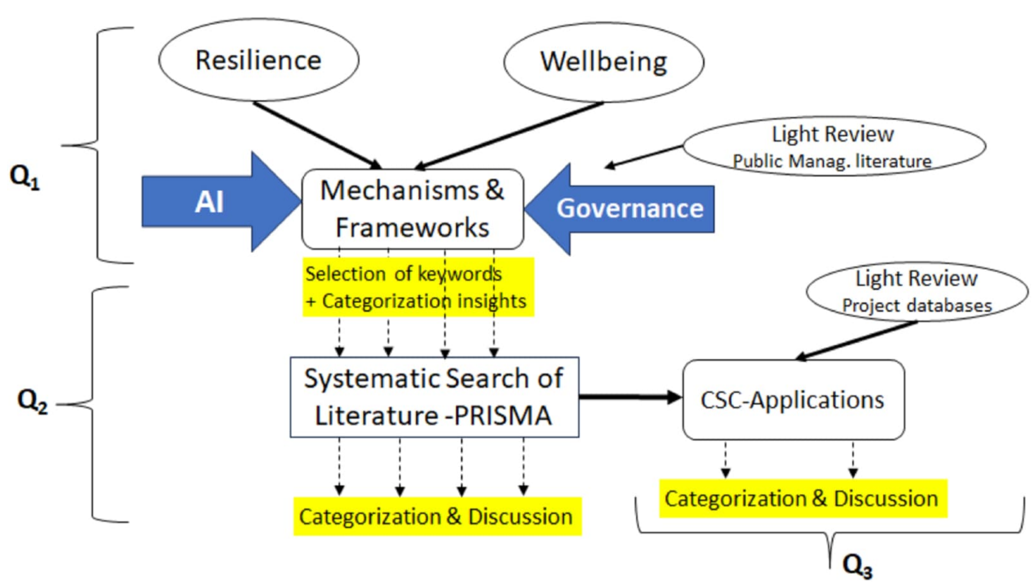

Fig. 1. High level description of the literature search employed in this paper. Dot lines refer to outcomes. Highlighted text indicates the output of each research question.

emphasize the complex interaction between internal attributes and external factors (Johnson, 2018; Masten, 2009).

In the popular Garmezy 's resilience theory (Garmezy, 1991), one distinguishes three important levels that play key role in resilience and wellbeing: i) *Level 1*: individual characteristics such as such as intelligence and temperament; ii) *Level 2*: family and the extent of support they provide to the child; iii) *Level 3*: external support from persons and institutions outside the child and the family, which include schools, community and public services. At each of the above three levels, one can also separate risk factors and protective factors. Table 1 provides some examples of such factors at each level. The recent research from Ungar and Theron claims the resilience in individual's life can also be facilitated by multiple promotive and protective factors and processes (PPFPs) at multiple systemic levels (Ungar and Theron, 2020). The presence of multiple risk factors can yield amplified effect, which negatively impact child resilience. For instance, poverty may leave children feel unsafe and undervalued, which can be exacerbated by resource-deprivation to community supports such as schools, healthcare and social services.

Some social psychology scholars link resilience with individual's capabilities, which are defined as the capacity of individuals to "do and be that which they have reason to value" (Nussbaum and Sen, 1993). This builds analogy between the concept of resilience and the idea of 'competence'; that is, competent people are defined as those who have the abilities "to generate and coordinate flexible, adaptive responses to demands and to generate and capitalize on opportunities in the environment" (Waters and Sroufe, 1983). From the perspective of systems, Ungar broadens the definition of the resilience to be a process of navigation to services and negotiation to have services provided in child-focused ways that sustain their wellbeing (Ungar, 2005). The importance of resilience-based focused intervention has shifted the effort of child welfare professionals from a deficit-based focus on safety and mitigation of problems to a more holistic approach of promoting the overall wellbeing of children and families (Masten and Obradović, 2006).

In terms of intervention-based approach for resilience building, Hromek and Roffey (2009) have noticed that social and emotional understandings and skills are dynamic and inter-related, underpinning both personal resilience and healthy relationships, which shape wellbeing. Such interventions can be implemented either as part of school curriculum or social work-based intervention policy, monitored by regional or national regulator bodies.

Table 1
Examples of risk and protective factors at each level.

Level	Risk Factors	Protective Factors
Individual	Prenatal brain damage Poor health in infancy Low intelligence Difficult temperament Chronic illness Poor social skills	Easy temperament Adequate nutrition Attachment to family Above-average intelligence Problem-solving skills Optimism
Family	Poverty / economic insecurity Parental unemployment Homelessness Divorce and family break up Family conflict	Supportive caring parents Family harmony Responsibility within family Strong family norms and morality
School & Community	Bullying Peer rejection School failure Truancy or dropout School transition Socioeconomic disadvantage Social or cultural discrimination neighborhood violence / crime	Sense of belonging/connectedness Positive school climate Opportunities for success & recognition of achievement School norms against violence Networks within the community Participation in community groups Access to support services

Crucial for practitioners and decision-makers are the assessment criteria that can be employed to evaluate child resilience and wellbeing. In this context, Windle et al. (2011) identified 15 distinct appealing measures of resilience but without "Gold standard"; an adaptation of the scale to children and youth has been proposed by Campbell-Sills and Stein (2007). Other studies measured resilience in terms of mental health, functional capacity and social competence (Olsson et al., 2003), or Hildon et al. (2008)'s quality of life measurement scale. Other national measures of relevance include UNICEF's 'child wellbeing' index (UNICEF, 2020). In education setting, one mentions the strengths and difficulties questionnaire (SDQ), also known as Youthinmind (Youthinmind, 2013), widely used across the UK institutions to measure the mental health of looked after children in schools.

2.2. Resilience and wellbeing at community level

Similar to individual resilience provided in previous subsection, a resilient organization is characterized by its ability to 'bounce back' quickly in case of unforeseen adversity (Wildavsky, 1988), allowing it to maintain a high-level performance even when a threat arises or uncertainty deepens. Especially, resilient organizations "keep errors small and improvise workarounds that keep the system functioning" (Weick and Sutcliffe, 2001).

Loosely speaking, the question whether the concept of individual resilience can be expanded to a community or an organizational level has been investigated by many scholars. Boin and van Eeten (2013) distinguishes two types of organizational resilience. First, precursor resilience, which prevents budding problem from escalating into full-blown crisis, is defined as the "ability to accommodate change without a catastrophic failure, or a capacity to absorb shocks gracefully" (Foster, 1993). The second type, referred recovery resilience, is defined as "the ability to respond to singular or unique events" (Kendra and Wachtendorf, 2003), bouncing back to a state of normalcy.

Boin and van Eeten (2013) pointed out that empirical research on resilient organization is quite rare with little knowledge about the causes of resilience or how it is achieved. Some elements of answers have been mapped by studying what was referred as high-reliability organization (HRO), like nuclear organizations, air traffic control centers. Failure in these organizations may trigger loss of critical societal functions and important damages. In this context, the resilience is ultimately linked to the concept of high reliability theory (HRT) in which the focus is shifted towards a clear awareness of core events, a culture of reliability, a formal structure of roles, responsibilities and reporting relationships (Bourrier, 2011; Rochlin, 2011). A second identified element behind the success of HRO is related to the process of reliability maintenance. Namely, once a threat emerges, HRO advocates the capacity to 'reorder' and 'reorganize' to deal with that threat (la Porte, 1996). This reordering involves a combination of rapid decentralization and facilitated improvisation. Thus, HRO offers a suitable framework for endorsing precursor resilience.

2.3. Impact of AI

The interaction of AI technology with children or youth is well-acknowledged through various channels. This includes recommender-systems that are embedded in toys, video games, music query systems, chatbots, search engine ranking of outcomes, social media friendship suggestion by employing sophisticated adaptive learning software and cookies management systems. This forces children to interact with AI systems that are not necessarily designed for them. This disruptive effect of AI conveys the risk of transforming children lives in a bad direction. Besides, surprisingly as reported by Unicef AI Children report (UNICEF, 2020), the possession of AI-enabled devices, like smart-phones, smart TV, tablets and intelligent gadgets becomes one of the pre-requisites for children well-being in the sense that a child who does not possess such devices often feels discomfort. In short, children's lives and well-being are indirectly impacted by the automated decision-making systems that often interact with several services associated to welfare subsidies, quality of health care and education access, and their families' housing applications. This motivates the Unicef's call for a more children-centred approach of AI.

2.3.1. AI-based governance

In public management, (Petrescu, 2019) proposed a public service theory by integrating technology-based service ecosystems and by combining theories related to systems, institutions, cognitive computing and collective intelligence in an optimized public service logic framework. The proposal incorporates the service ecosystems view into the Public Service Logic (PSL) and focusing on the co-creation of value at micro, meso, and macro level, as well as promoting interactions among stakeholders in the value of co-creation process. The potential impacts of digital technologies and AI on co-production and co-creation (with interaction with citizens) have also been pointed out in Lember et al. (2019) conceptual model. Wirtz and Müller (2019) advocated a layer based conceptual framework, distinguishing technological, regulatory and ethical layers. Kattel et al. (2020) highlighted the importance of human-computer collaborations to achieve digital public service

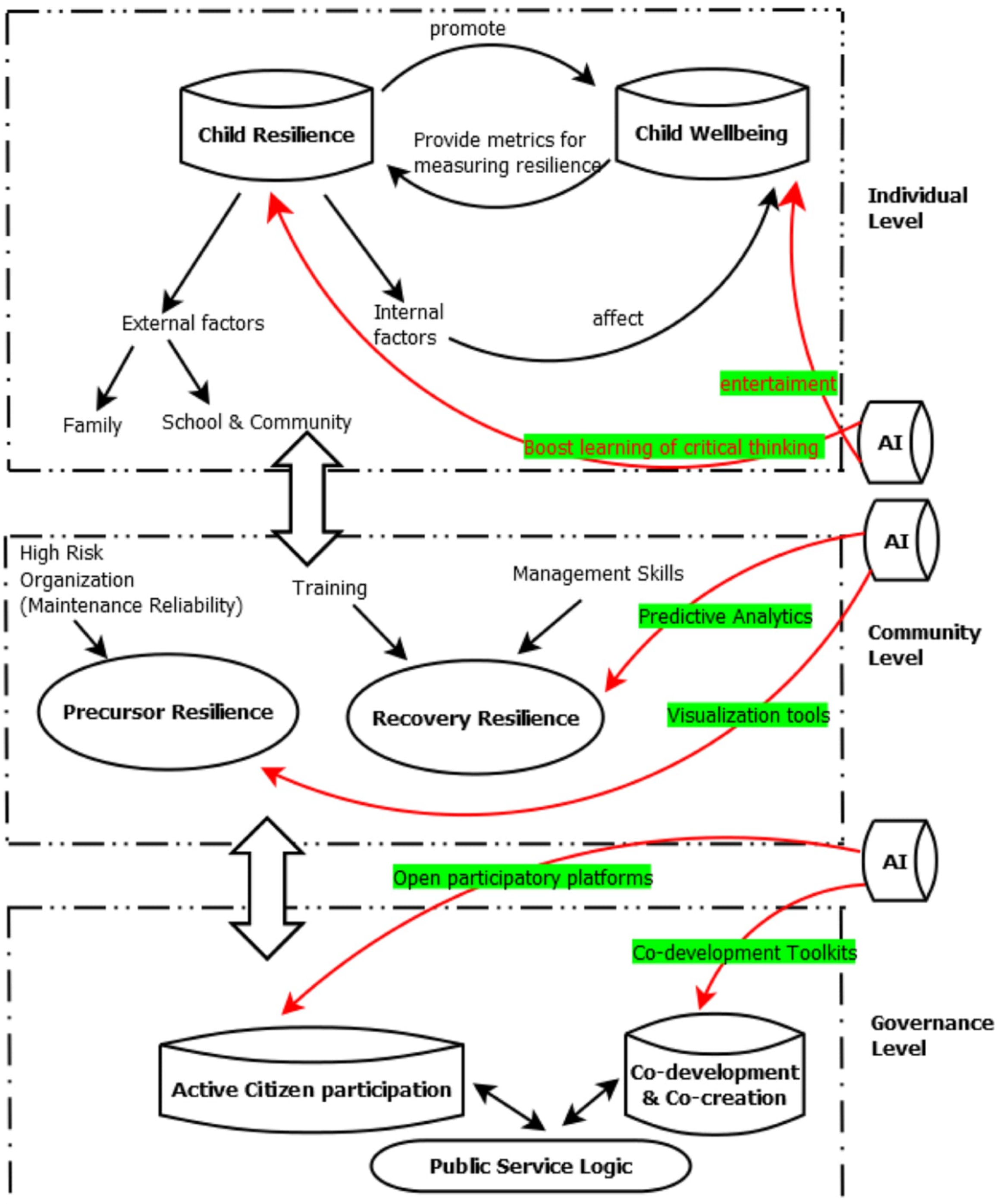

Fig. 2. AI CSC governance interlinking individual resilience / wellbeing factors to community and governance level. Red arrows indicate contribution of AI-based tools, while highlighted texts (in green) point to the mechanism underpinning this contribution.

efficiency. In terms of the explored public services, health and wellbeing sectors are often cited among the primary target of AI due to the availability of large scale and useful data resources, see, e.g., (Finnish AI Report, 2019). Therefore, this implicitly expects AI governance framework to contribute to individual resilience and wellbeing especially in CSC sector. In an attempt to link Lember et al. (2019)'s AI-based co-production and co-creation framework, Kattel et al. (2020)'s interactive model to the individual & community level of resiliency and wellbeing handling, while capitalizing on the strength of HRO, Fig. 2 summarizes our findings for interlinking individual resilience / wellbeing to community and governance, providing a high-level skeleton that answers *Q1*.

3. Methodology for systematic review-based approach

Now given the sparsity of research into the connection between AI technology and governance of children social care (including psychosocial care) with its impact on resilience and wellbeing, and in order to go beyond the public management community, a systematic literature survey was conducted. We adopted PRISMA framework for this purpose (Moher et al., 2009). More specifically the methodology deployed four processes consisting of:

(1) *Identification* of search databases and query. In our case, we have used Scopus, IEEE Xplore, ProQuest and Google scholar as search databases. This is motivated by their wide-spread use in humanities, social-care and artificial intelligence research. The search criteria are partitioned into five categories (Target group, AI technology, Resilience/Wellbeing, CSC domain, Governance) where for each category a set of representative keywords has been identified. Therefore, the input database search consists of an OR-logical combination of keywords of individual category followed by an AND-logical combination over individual category outputs. See, Table 2 for details on the search queries employed where the key attributes of AI-based CSC governance as discussed in Section 2 have been taken account.
(2) *Screening:* This is performed by combining the search results of different databases and removing duplications. Also, the results that do not contain abstract are removed.
(3) *Eligibility:* This filters out the search outputs according to the exclusive/inclusive criteria set. Initially, the inclusion criteria were twofold. First, the query search is said positive if at least one keyword of each category is found in the title, abstract or keyword-list of the paper. Second, we restrict to English-written papers whose publication date is between 2000 and 2023.
(4) *Inclusion:* This compiles and stores the gathered selected papers for a final analysis.

Table 2
Keyword categorization for the query search.

Category	*Keywords*
Target Group	("child*" OR "youth" OR "adolescent*" OR "student*")
AI Technology	("Artificial Intelligence" OR "AI" OR "big data" OR " machine learning" OR "deep learning" OR "expert system" OR "predict*" OR "recommendation system" OR "chatbot" OR "virtual assistant" OR "robot" OR "rule-based system" OR "fuzzy reasoning" OR "case-based reasoning" OR "decision support system" OR "decision making system" OR "natural language processing" OR "genetic algorithm")
Resilience/ Wellbeing	("resilience" OR "psycho*" OR "psychiatry" OR "mental health" OR "well-being" OR "adaptation" OR "vulnerab*" OR "happiness")
CSC Domain	("social service" OR "social welfare" OR "social care" OR "social work" OR "child care" OR "child welfare" OR "health" OR "education" OR "family")
Governance	("governance" OR "management" OR "organization")

The above process has been automated by utilizing the available API search of each of the four databases (Scopus, IEEEXplore, ProQuest, Google scholar) and by monitoring the API output, which consists of paper's title, abstract, list of keywords, authors and affiliation, citation and link to the full paper.

In the eligibility phase, the abstracts of individual papers are examined to ensure each category is fulfilled in the result. This narrows down the search. A graphical illustration of this process is provided in Fig. 3.

Additionally, to answer Q3, the potential results that may arise from the above PRISMA analysis are augmented by a set of external references, consisting of European Commission AI technical reports, AI Watch and EU project database (CORDIS), to compile a non-exhaustive list of AI-projects or AI-initiative in CSC field.

4. Results

A total 49329 search results have been generated by the databases of Scopus, IEEE Xplore, ProQuest, and Google Scholar. 440 articles related to resilience, well-being and AI-governance were finally included in the systematic review after being filtered out according to the defined inclusive / exclusive criteria. Next, a manual check has been carried out to identify for each record to each class it contributes most; namely, resilience / wellbeing through individual, family or school / community related factors or CSC governance. In this respect, 325 studies are found mostly linked to resilience/wellbeing issues and 115 studies to AI CSC governance. A yearly evolution of the outputs for each category (individual, family, school/community) is provided in Fig. 4 We also displayed in Fig. 5 the yearly evolution of studies in CSC-governance alone.

As it can be seen from Fig. 4, there is a steady increase in the number of publications in overall (with the exception of the year 2023 that is not yet fully accounted for), especially since 2016–2017, which corresponds to the time where first AI ethical legislation arises both in EU and USA countries. Besides, the graph shows the dominance of individual based resilience studies as compared to the community and family level. This partly explains the mixture trend of number of CSC governance studies observed in Fig. 5, which exhibits a peak in 2019 followed by a sharp decrease, and then an increasing trend again.

Next, we followed de Sousa et al. (2019)'s categorization of AI techniques applied to public services which emphasize machine learning (ML), neural network (NN), natural language processing (NLP), robot, Expert Systems, Fuzzy logic, and general algorithm basic construction as the main implemented AI methods. Therefore, we plot in Fig. 6 the distribution of studies with respect to the AI-techniques employed. The results indicate the dominance of machine learning followed by Robot-based reasoning in the surveyed studies.

4.1. Review of AI studies in child resilience and wellbeing

In addition to the individual / community-based categorization, we borrowed the risk / protective factors classification highlighted in Table 1 to further categorize the studies falling on either individual or family/community categorization. In other words, prior to setting a new categorization for a given study according to its content and the approach taken for AI-governance, we first look whether one of the categorization pointed out in Table 1 can be mapped. The results of this scrutinization shown in Table 2. In terms of AI techniques employed, ML is found in areas such as child welfare (Negriff et al., 2022; Zytek et al., 2021; Schwartz et al., 2017), child abuse (Amrit et al., 2017), disease diagnosis (Ben-Sasson et al., 2018), child health behavior (Dugan et al., 2015) and education (David and Balakrishnan, 2010), etc. In School and Community settings, many reported studies have been found to use robot-like AI techniques to provide a personalized teaching support due to their interaction capabilities.

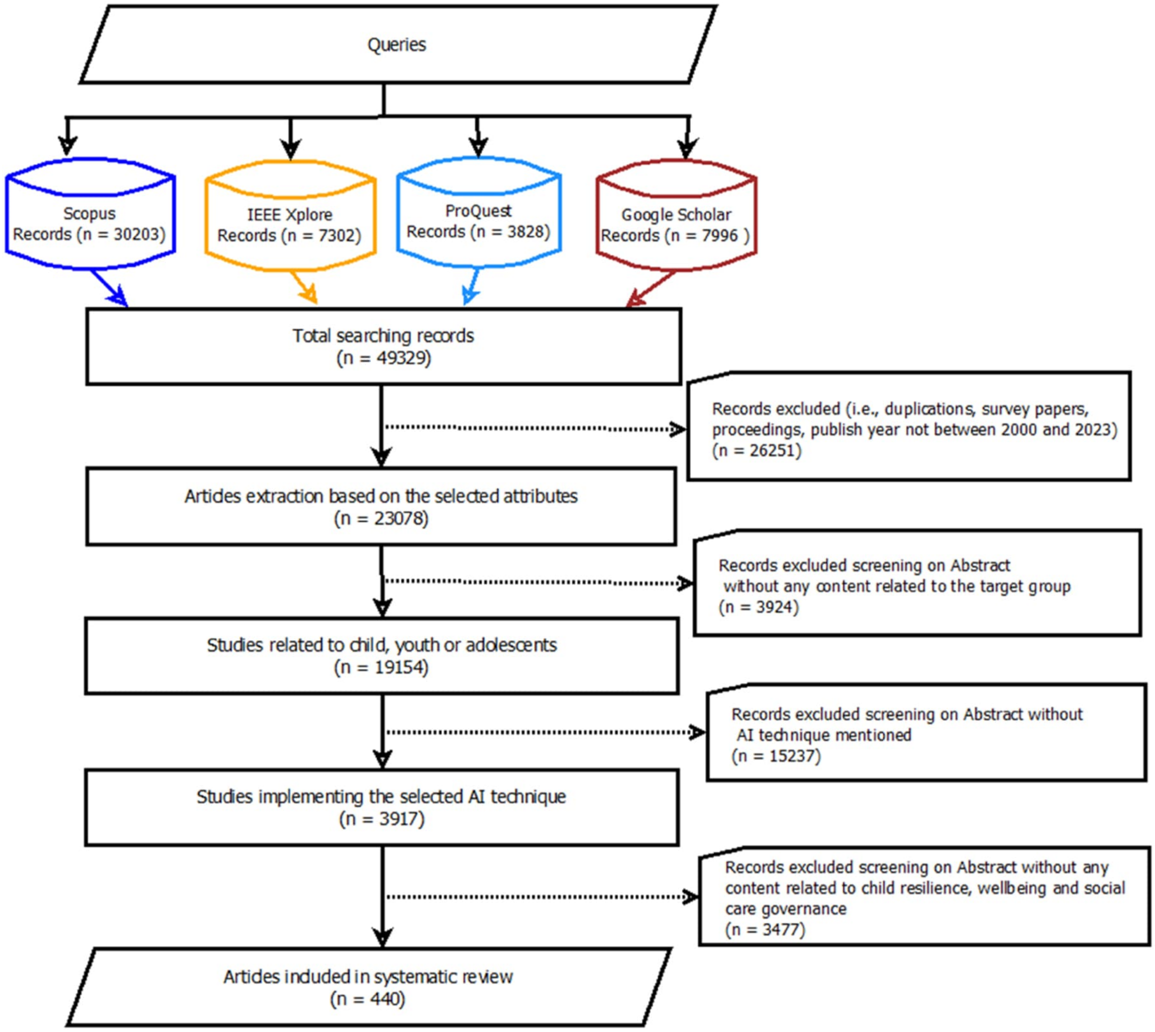

Fig. 3. PRISMA flowchart for the selected studies.

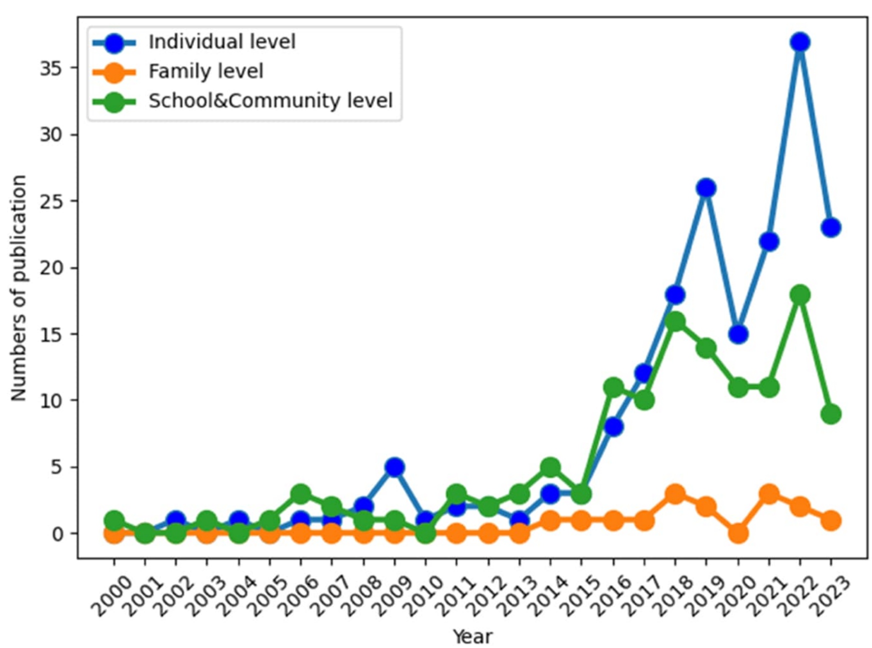

Fig. 4. Number of AI studies in child resilience and wellbeing from three-levels characterization.

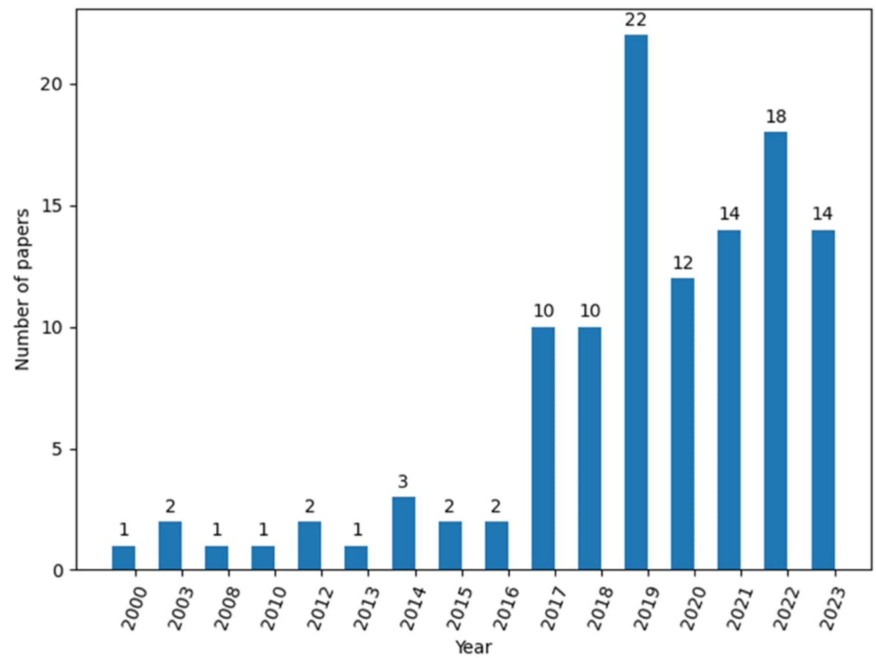

Fig. 5. Number of AI related studies in CSC governance.

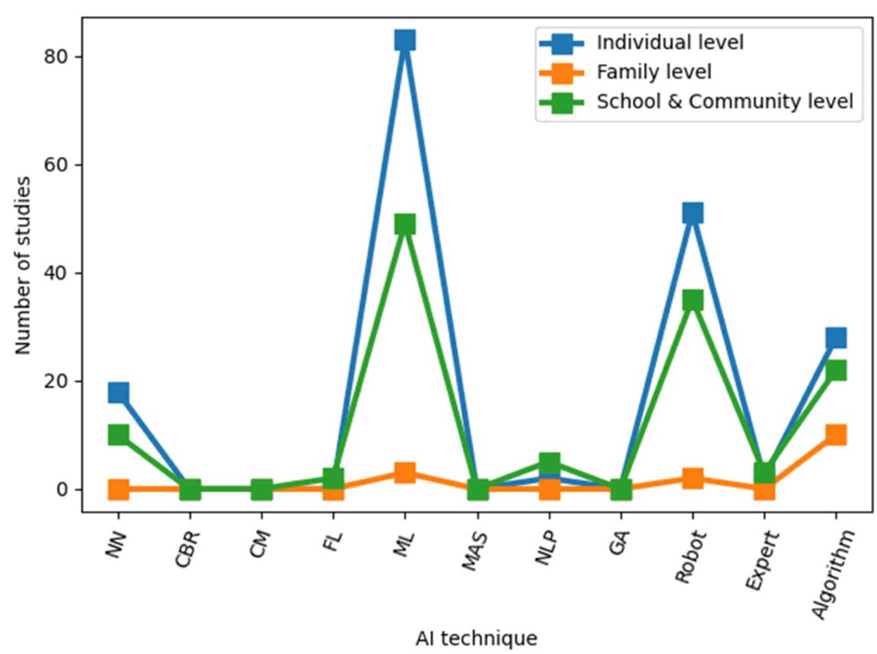

Fig. 6. AI technique applied in child resilience and wellbeing (NN: neural network, CBR: case based reasoning; CM: cognitive mapping; FL: Fuzzy logic; MAS: multi-agent system; NLP: natural language processing; GA: genetic algorithms; Expert: Expert systems).

4.1.1. Individual level

Among the 325 articles, 184 AI-based intervention studies in child resilience and well-being were identified to rather refer to individual factors associated resilience. Most of these studies focused on psychological well-being (e.g., Autism, emotion, mental health, depression, attention, ADHD, suicide), coping with skills and learning ability, management style (personality, self-esteem, stress). Intuitively, many of such categories are either implicitly or explicitly linked to child resilience or wellbeing. For instance, mental health is acknowledged as a level of psychological wellbeing which affects how we think, feel and handle unforeseen situations according to World Health Organization (2018). Depression (e.g., Haque, Kabir and Khanam, 2021; Radford-Smith et al., 2023), suicide (e.g., Drousiotis et al., 2023), ASD, ADHD and stress (e.g., Aalbers et al., 2023) are distinguished instances of mental health diseases or behavior. Emotional health is another important part in overall health of children and adolescents, where computer vision-based recognition can be of paramount importance to identify cases that cannot be straightforwardly discerned by parents or careers due to inappropriate vocabulary usage for instance as in Gamborino et al. (2019) or Wang et al. (2021). Besides psychological well-being, coping skills (referred as children's social and interaction skills) and learning ability are among important recipes that are found critical to promote child resilience nowadays. In terms of AI techniques, ML and robot are widely dominant as highlighted in Table 3. For

Table 3
AI techniques applied in resilience from individual level, family level and School / Community levels.

Category	AI technique							Total
	NN	*ML*	*NLP*	*Robot*	*Expert System*	*Fuzzy logic*	*Algorithm*	
Individual Level								
ASD	3	14	1	8	1	0	1	31
Emotion	1	9	0	10	0	0	1	21
Coping skills	0	3	0	11	0	0	1	15
Learning ability	3	5	0	3	0	0	1	12
Mental health	5	20	0	11	1	0	7	44
Depression	1	8	0	0	0	0	1	13
Others	1	17	1	2	0	0	5	26
Suicide	0	3	0	0	0	0	3	6
Attention	1	1	0	2	0	0	1	5
ADHD	0	0	0	0	0	0	1	1
Fatigue	0	0	0	1	0	0	0	1
Personality	1	0	0	0	0	0	0	1
Self-esteem	1	0	0	0	0	0	1	2
Stress	1	3	0	2	0	0	0	6
Total	**18**	**83**	**2**	**51**	**2**	**0**	**28**	**184**
Family Level								
Homeless	0	0	0	0	0	0	5	5
Child abuse	0	1	0	0	0	0	1	2
Healthcare	0	0	0	0	0	0	2	2
Education	0	1	0	1	0	0	0	2
Family structure	0	0	0	0	0	0	1	1
Parenting	0	1	0	1	0	0	1	3
Total	**0**	**3**	**0**	**2**	**0**	**0**	**10**	**15**
School / Community Level								
Interactive teaching	2	6	2	31	2	1	0	44
Supportive environ.	4	15	0	2	1	0	8	30
Unhealthy content	1	9	1	0	0	0	4	15
Performance	1	7	0	1	0	0	2	11
Child abuse	0	4	1	0	0	0	6	11
SUD	1	4	0	0	0	0	1	6
Bullying	1	2	1	0	0	1	0	5
Crime	0	2	0	1	0	0	1	4
Total	10	49	5	35	3	2	22	126

instance, ML was used to predict factors and treatment issues associated to mental disorders (Vaishnavi et al., 2022; Bzdok and Meyer-Lindenberg, 2018). Srividya et al. (2018) applied various ML approaches to identify state of mental health of an individual from different groups (high school, college students, and working professions). In social context, robots have been suggested to enhance social intervention to treat children with ASD (Joseph et al., 2018; Ferreira, 2022).

4.1.2. Family level

As one of the protective factors, Khanlou and Wray (2014) characterized family level resilience through existing family structure & cohesion, parent-child interaction, family environment at wide with their economic, education and professional prospects. Our review identified 15 AI studies related to family level resilience, mostly focusing on algorithms implemented to the homeless populations related to HIV diseases (Rice et al., 2018; Yadav et al., 2015, 2016), parenting (Lakhdir, et al., 2021), substance use disorder (Tabar et al., 2020) and shelters information prediction (Hong et al., 2018). In the minimum living standard security system, k-means algorithm was applied to classify the low-income families which give some suggestions for poverty alleviation (Deng et al., 2016). Lakshmanan et al. (2019) studied the impact of income healthcare support for families to improve transition from nicu-to-home for infants. AI techniques were also implemented in parenting support, for instance, risk factors identification in child maltreatment (Murry and Lewin, 2014), storytelling robot application in parenting (Lin et al., 2021), machine learning in parental relationship study (Hu et al., 2023), and adaptive instruction conducted in virtual simulations and game-based platforms (Sottilare, 2018). For instance, Deng et al. (2016) identified the key characteristics of low-income groups from the minimum living standard security system using K-means algorithm and provided accordingly some suggestions for family poverty alleviation. From a conceptual framework, several papers were found to refer to Walsh's family resilience model (Walsh, 2003) that encapsulates three-class attributes (belief system, organizational pattern / communication and problem solving) and focusing on strengths under stress in the midst of crisis and ability to overcome adversity.

4.1.3. School / community level

From school & community level, 126 studies were identified and then classified into seven categories of intervention: interactive teaching, supportive environment, unhealthy content, child abuse, substance user disorders, bullying and crime as highlighted in Table 2. The dominant technique implemented in this level is ML with 49 studies, robot with 35 studies and algorithm with 22 studies.

ML has been implemented in studying students' emotional wellbeing (Asadullah and Tham, 2023) during school closure due to new challenges brought into education system by COVID-19. Students' wellbeing has also been affected by the shift in education from traditional face-to-face learning to e-learning. ML and artificial intelligence-based analytics have been conducted to study the impact of online learning on students' psychological well-being (Rezapour and Elmshaeuser, 2022; Abalkheel, 2022). In school domain, robots were mainly used for improving interaction during teaching and providing supportive environment for children. Interactive simulation robots can be tailored for social, educational, rehabilitation, therapeutic and entertainment purposes as examined in Libin and Libin (2004)'s review paper, social skill training for children with special needs (Cao et al., 2017; Conti et al., 2020; Newbutt et al., 2022). School bullying is acknowledged as another critical factor among teenagers that can cause depression, dropping out of school, or even a suicide. ML and NLP were among the main approaches for bullying identification (Haidar et al., 2017). Additionally, the literature review covers 11 studies focused on the analysis of students' academic performance including several facets like academic outcomes, school dropout, cheating, etc. For instance, ML techniques have been deployed in predicting students' success (Fahd et al., 2021; Arizmendi, et al., 2022; Han, 2023), academic cheating (Alsabhan, 2023), and dropout (Mariano et al., 2022).

In community level, a special interest focused on preventing children from the dark effects of social media and internet communication at wide, which can easily impact youth behavior towards violence or mental health issues. Detection of violence using ML techniques from youth social media posts are examined in (Khan et al., 2018), or adult content in (Gajula et al., 2020; Moreira and Fechine, 2018), and suicidal ideation detection in (Sawhney et al., 2019). Child abuse or child maltreatment is also found preeminent in our study where ML and NLP techniques were advocated in (Amrit et al., 2017; Rosenthal et al., 2018) for child abuse detection; bullying detection in (Aggarwal et al., 2020; Haidar et al., 2017); SUD risk quantification (Tabar et al., 2020).

4.2. Review of AI related studies in CSC governance

We identified 115 studies that provide a global picture of the current trends of CSC AI-based governance (see, Fig. 5 for a yearly output), associated challenges, policy requirement and AI technology involved (see, Fig. 7 for summary of AI-techniques involved). We further investigated the question of what is the main purpose for introducing AI-tool (s) in CSC governance in each of these studies. The manual scrutinization of the 115 studies revealed seven key reasons or classes of answers:

- *Risk assessment*: This covers, for instance, issues associated with predicting whether placing a child in a foster home or a care is appropriate or not. With the availability of historical data pertaining to family demographic and economic data, AI is, for instance, embedded in predictive risk modeling tools for classifying risk in child protection agencies (Cuccaro-Alamin et al., 2017).
- *Administrative data system*: This concerns the architecture and organization of child welfare data system indicating the various topical and demographical variables, structure of archival records, among others, and importantly, the ease and the scope of the associated query systems. AI can therefore be used to provide advanced and intelligent search capabilities as well as linking with other external and open data, pushing forward with big data analytics (Shen et al., 2012).
- *Community building*: AI tools can be used to increase the interaction with various communities involved in child welfare (e.g., parents, specialized health services and care, frontline workers). NN technique was implemented successfully in modeling administrative data from Washington State Child Protective Services using 37 risk factors to predict child abuse risk by Marshall and English (2000). Stolk and Nyon (2017) proposed a theoretical decision support system DIONE to optimize health and social service intervention by integrating all the data available in child protection agency. Virtual assistants have been suggested for generating automatic feedbacks and detecting potential criminal activities in BotHook (Zambrano et al., 2017).
- *Resilience*: Various refinements of Organizational Resiliency Model (ORM), originally developed by the University of Texas in 2009 and dedicated to child abuse field have been proposed with integration of AI-based techniques. AI was used to quantify, deploy and validate various data gathering and analysis methods. We also distinguish the three-level resilience capacity of Oxfam framework (absorptive, transformative and adaptive capacity), see, e.g, (Jeans et al., 2016).
- *Policing*: The raise of evidence-based policing provides a sustainable ground for applying AI techniques to generate evidence for backing a given child-welfare policy related agenda. For instance, Stolk and Nyon (2017) proposed a theoretical decision support system DIONE to optimize health and social service intervention by integrating all the data available in child protection. See, also (Gillingham, 2019b) for DSS implementation.
- *Implementation*: This concerns the process of introducing AI technology in child welfare system governance, highlighting the bridge from theory to concept and from prototype to a large-scale implementation, appropriate measures of effectiveness, deficiency gaps, etc. This determines the scope and extent of the social innovation brought by the AI. We distinguish, for instance, disruptive, incremental, sustainable and radical like-transformations (Misuraca and Viscusi, 2020) that can be employed to derive pilots for implementation purpose.
- *Trust*: This builds on the observation that due to the evolving regulatory landscape, especially, the European Union's GDPR on the "right to explanation" (Goodman and Flaxman, 2017), the potential complexity of AI technology can raise trust and transparency issues

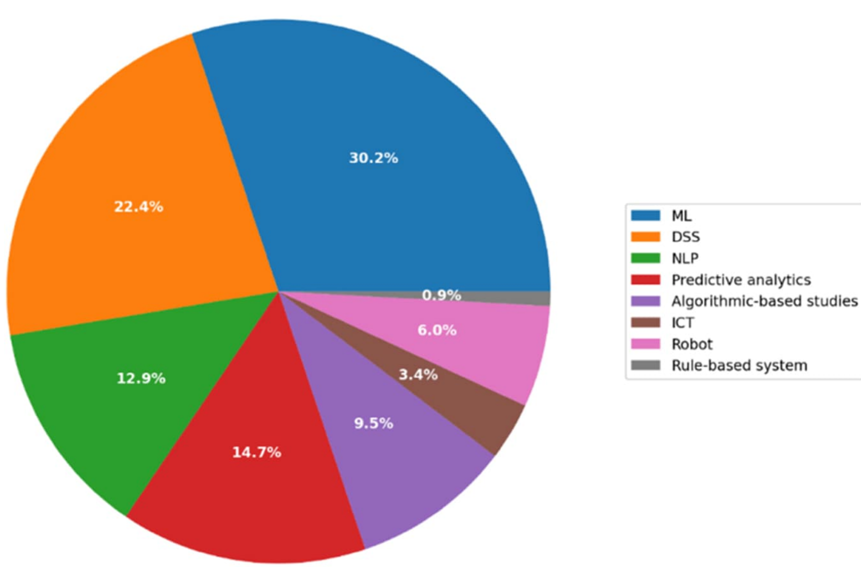

Fig. 7. Statistics of tails of AI related studies in CSC governance.

with citizens and stakeholder chain. Therefore, a substantial research effort has been devoted to exploring this issue using AI ethics and the emerging interpretable AI models (Guidotti et al., 2018).

Central in each of the above categorization are the metrics employed for the assessment and quantifying the underlined evidence. In this respect, one mentions the growing recognition within governance scholars of the *Public Value* gained by the implementation of the AI

Table 4
Categorization of AI CSC governance studies and key innovations.

Category	Focus	Main AI techniques	Reference samples
Risk Assessment	Estimate likelihood of child abuse, Risk of removal and preventive interventions	ML (60%), NN (15%), Fuzzy Logic (10%), Others (15%)	Dare et al. (2012);Cuccaro-Alamin et al. (2017a);Schwartz et al. (2017); Vaithianathan et al. (2017);Chor et al. (2022);Barmomanesh and Miranda-Soberanis (2023)
Administrative data system	Architecture of administrative data system, query systems	Data and text mining (70%), robot (10%), Others (20%).	Shen et al. (2012)
Community building	Improve interaction & communication with citizens and various stakeholders	Robot (30%), ML (25%), DSS (15%), Others (30%)	Stolk and Nyon (2017);Zambrano et al. (2017);Gillingham (2019a)
Resilience	Build organizational resilience that enhances individual resilience.	ML (40%) for risk estimation; Robot (25%) for interaction; Others (35%)	Arthur et al. (2007);Fagan et al. (2010);Jeans et al. (2016)
Policing	build tools for evidence-based policing and enhance active citizenship	ML (25%), Robot (25%), DSS (20%), Other (30%)	Stolk and Nyon (2017);Gillingham (2019a); Gillingham (2021);Meilvang and Dahler (2022);James et al. (2023).
Implementation	Iterative process of AI concept implementation and assessment metrics	DSS (28%), NLP (25%), ML (15%), other (32%)	Misuraca and Viscusi (2015);Goodman and Flaxman (2017);Coombs et al. (2021);Lepri et al. (2021).
Trust	Handle AI interpretability, safety, privacy and accountability.	ML (40%), DSS (20%), NLP (20%), other (20%)	

Key innovations in AI-CSC governance (CB: Community Building; ADS: Administrative Data System; R: Resilience; RA: Risk Assessment; P: Policing; I: implementation)

Innovation	*Link / reference*	*Focus*	*Category*	*Limitation*
Medical passport System at Denver, Colorado Child Welfare agencies	Innovative Technologies in Child-Welfare Services, SACHS (Hughes, MSN, 2018)	Data sharing system and high secure architecture to preserve privacy.	CB	Require supporting health infrastructure system.
FAMCARE.net at Michigan state.	Moving Up in the New Economy, Career Ladders for US Workers (Fitzegrald, 2006)	Platform for sharing data between welfare agency, court and health agencies.	CB	Require coordination effort
Online Warrant Tracking System, by Illinois, DCFS	https://www2.illinois.gov/dcfs/safekids/reporting/pages/index.aspx	web based system that tracks warrant applications (take children to protective custody	CB +ADS	Output requires further checking to avoid algorithmic bias.
iFoster national portal	https://portal.ifoster.org/	Help foster youth to build their network and succeed	CB+R	Depend on user willingness to interact.
FosterClub Facebook	https://www.facebook.com/-FCAANational/	Use facebook to connect youth foster to boost their education and career	CB	Depend on user willingness to interact.
Binti application	Cuccaro-Alamin et al. (2017b)	Build foster family approval to handle shortage of foster parents	R + P	Require family collaboration
Rapid Safety Feedback, by Eckerd Kids	https://eckerd.org/rapid-safety-feedbacks-rapid-ascent/	Predictive analytics tool for risk assessment	RA+P	Require checking for algorithmic bias
Washington's Visitation Program	The Chronicle of Social Change With Fostering Families Today (2017)	Visualization toolkit to help CSC managers in decision making	P	Requires good skill to interpret the graph
GoCase Virtual Reality App by Deloitte	Payne (2017)	Allows social workers to assess the safety and risk factors inside of a family's home.	RA	Limited number of factors are accounted for.
Child Protection Simulator by Kent University	The Centre for Child Protection (2021)	Provide training to child welfare staff and agency to reduce staff mistakes.	RA	Only limited number of factors are accounted for.
Statewide Automated Child Welfare Information System (SACWIS)	SACWIS/TACWIS Information (2017)	organize caseworker caseloads at national level (USA)	ADS	Tailored to USA national health system.
Think of Us platform in California	Brindley et al. (2018)	Enable youth to create goals (finance, family, mental health) and enable caseworker to create transition independent living plan	ADS + CB	Requires high level expertise to interpret the outcomes
SyRi system in Netherland	https://cordis.europa.eu/- project/id/609138	Detect fraud in welfare system using AI algorithms.	RA	Transparency issues- caused its interruption,
AuroraAI in Finland (FI)	https://vm.fi/en/auroraai-en	Large scale Finnish national program to implement AI in public services tailored on citizen needs.	ADS + CB +I	Lack of maturity and scalability of solutions.
Robotic Process Automation at Treleborg municipality (SW)	Ranerup and Henriksen (2019)	AI-Automatic decision making tool for managing application to homecare, fostering, sickness benefits	ADS + RA	Require substantial manual check
Service Path Prediction, Espoo municipality (FI)	Engels et al. (2019)	Use of AI tools to predict service path of each individual using health dataset from Kela dataset	RA	Used at limited scope only and require update.
AI for parallel Society, Gladsaxe, Denmark	https://algorithmwatch.org/en/automating-society-denmark/	AI tool to tackle vulnerable areas (parallel society) for automatic recognition of children in needs.	RA	High false positive reported
Kind & Gezin, Flemish public agency, Belgium	https://vbjk.be/en/partners/kind-gezin	Predictive AI tool to identify daycare services in need of further inspections	RA	Require manual check and regular updates.
AlterEgo artificial agent	https://cordis.europa.eu/project/id/600610	Software agent and virtual reality for improving social interaction, especially for dealing some youth mental health issues	CB	More tailored for youth with
Online Compliance Intervention, Aust. Welfare Agency	ESCAP (2019)	Machine learning method for fraud detection in welfare systems	RA + P	High error rate and increase cost of manual scrutiny.
TalkingPoints, Google AI project	*https://talkingpts.org/what-we-do/*	Capacity building framework for family-school partnership	CB+RA+R	Used on voluntary only.

governance service. This aims to assess the social value the underlined technology is able to bring to citizens, society and governance administration (O'flynn, 2007). Three general value drivers to assess the impact of ICTs within the government from a public value perspective are Performance, Openness and Inclusion (Misuraca and Viscusi, 2015; Twizeyimana and Andersson, 2019). Table 4 summarizes the key findings regarding each of the aforementioned category as well as the main AI governance achievements in CSC field. The findings clearly point out the lack of innovations in “Trust” and “Implementation” categories. In addition to the 115 studies emerging from the systematic literature we also carried out extra search on European Commission AI technical reports, AI Watch and EU project database (CORDIS) to identify projects implementing AI-based CSC governance.

5. Discussion

5.1. Scope of AI implementations

Acknowledging the fact that AI-CSC governance is not only about developing a more accurate and complex IT infrastructure using advanced AI algorithms that capitalize on a continued datafication of society and digitalization of government services, but also building the required ecosystem that puts active citizen engagement into the loop and draws a suitable regulatory framework, one shall notice the following:

- The predominant share of AI-CSC governance initiatives, innovations and publications lie in the data algorithmic section where new AI-based modules are integrated either to support CSC managers in their decision making process (e.g., new risk assessment approach, automatic categorization of the request, prediction analytics tools) or increase the interaction with citizens by optimizing time resources and taking advantage of new communication technology tools (e.g., automatic voice analysis to forward request to appropriate service, digital assistant tools that use speech and natural language processing, intelligent tutoring services, mobile apps).
- The preceding is in line with the recent Misuraca and van Noordt (2020)'s review report of AI-governance initiatives in EU where an evaluation in terms of the three value drivers (Efficiency, Inclusion, Openness) has been performed. The authors claimed that a mapping of current AI-initiatives in terms of their initial goals indicates the current EU AI-initiatives have been implemented with Efficiency gains as a primary target (70%) followed by Inclusion (27%) and Openness (3%).
- From a CSC perspective, any child fatality or severe maltreatment cases are horrifying events that fuel moral outrage, generate post-traumatic stress to CSC workers and intense political debate. This led, for instance, some US municipalities to stop using AI analytical tools because of high positive rates, and the Australian parliament to order stopping use of automatic fraud detection systems. This testifies on the required cautious attitude and fine-analysis of AI technology maturity level before its introduction to CSC field.
- Many child maltreatments and abuse cases are quite sparse and unique, the development of efficient training database is thereby made difficult. This, in turn, negatively impacts the performance of ML models. On the other hand, AI analytical tools for predictive analytics are dependent on the predictor variables employed to structure the initial dataset and generate features. Typically, these are coined around Child Behavior / Emotional Needs, Child Risk Behavior, Traumatic Experience (Saxena et al., 2020). However, the exhaustive listing and potential weighting of such variables is rather subjective and may vary from one organization to another, which directly impacts the outcome of AI algorithms as well. This partly explains the reported discrepancy of risk analytical tools such as FRAAN used in Michigan state, FRA in California (Jagannathan and Camasso, 2013).
- Most of AI tools require appropriate inputs from the users to provide acceptable outputs. However, due to cultural norms, language literacy, inherent language ambiguity and time constraint, this may be subject to fault and limitations as noticed at review of Australian automatic fraud detection system, for instance.
- In terms of resilience, several of the aforementioned initiatives are implicitly dedicated to boost child resilience at different levels. For instance, Espoo municipality Service Path in Finland can be categorized as a social innovation focused on adaptive resilience type; Robotic Process Automation of Trelleborg (Sweden) focused on absorptive type of resilience; Kind & Gezin in Belgium deals with absorptive resilience; AI for parallel society in Denmark is a social innovation that emphasizes transformative reliance type. In several implemented models, resilience factors were embedded into the designed risk factor model (e.g., Vaithianathan et al., 2019; Rodriguez et al., 2019).
- From an educational perspective, one shall mention in this context, TalkingPoints (Google AI project), which implements a dual capacity-building framework for family-school partnerships for enhancing family engagement that can be used to enhance resilience-based education.

5.2. Policy mitigation

Improving the governance of child welfare system is the primary target of the policy and management research. The introduction of AI tools as (aid) to decision-making system, boosting collaboration and interaction with citizens/stakeholders, risk assessment or data analytics tasks has provided ground for applying evidence-based policing (EBP) in child welfare systems. Scrutinizing the technical papers and initiatives identified in this area revealed that the quasi-majority lack the detailed analysis from policy-making perspective, and rather focus either on stressing the importance of AI-governance or suggesting conceptual framework (s) for AI governance implementation. Nevertheless, the research still lacks the theoretical premises that links child welfare system practices with established governance policy theories (e.g., argumentative theories, cultural theory, democratic and legal theories, network theories (Ansell and Torfing, 2022)) as well as the state of art knowledge in AI framework and social science.

In overall, there is a recognizing need for the widespread use of evidence-based practices (EBPs) that can prevent child abuse and improve the wellbeing of youth in the surveyed literature. However, the challenges for applying EBPs cannot be hidden, especially among ethnic minority children (Kathleen Sebelius, 2013). The need to identify appropriate theory-driven conceptual frameworks that pinpoint ‘implementation drivers’ yielding to successful EBP implementation, especially when targeting child mental health / child maltreatment interventions (Gopalan et al., 2014; Metz et al., 2015)is highly voiced in public-governance research community. In this context, (Hanson et al., 2016) reviewed ten frameworks in the context of child welfare use, highlighting the importance of planning and preparation for the implementation as well as the importance of inner / outer contextual factors that should constraint the implementation stage.

Finally, it is worth questioning to which extent the human-machine collaboration can be pursued and integrated as part of AI-governance framework. This arises from the variety of the identified AI tools, which include a recommender system-like approach where the user still can bypass the system recommendation in the decision-making process and a fully automated system where the operator cannot bypass the system output, passing through all semi-supervised scenarios which defined various level of human-system interactions.

5.3. Challenges, ways forward and Limitations

5.3.1. Unstructured data and ethics

Although it is true that the current digital administration of child welfare system together with active e-government services have given raise to large amount of big data that can be utilized to generate new knowledge and insights for evidence-based policy, the quasi-majority of such datasets are unstructured and non-linked. This poses serious questions on relying on such data to derive high impact decisions, which requires a special care to account for reliability, consistency and accuracy as part of the data analytics scheme. Furthermore, issues dealing with fairness, accountability, and transparency (FAT) impact both the approach tackling the unstructured data and the decision-making outcome of the AI algorithm. These are cited as tremendous challenges for the implementation of AI-governance in child welfare, especially when high levels of marginalization or social inequality is experienced (e.g., Munro, 2019). From a theoretical perspective, IEEE Global Initiative on Ethics of Autonomous and Intelligent (IEEE, 2017) provides useful recommendations for dealing with AI ethical challenges. Similarly, the EU High-level Expert Group provided a roadmap for designing trustworthy AI services in the public sectors (Drobotowicz, 2020), which can be adapted to some extent to child services as well. Recently the European Union has been working on the draft for Artificial Intelligence Act (AI Act) namely as the first regulation on AI to establish different regulations for different risk levels (Ebers, 2021). One of high-risk area is biometric identification and categorisation of natural persons, which should be considered in child social care. Another issue that strikes the development of effective AI-policy governance is rooted back to the rapid change of AI technology, which constraints the capacity of regulators to create a comprehensive regulatory framework. This suggests some preference to process based representation for policy cycle as in (Höchtl et al., 2016).

5.3.2. *Data representativeness*

CSC administrative data is primarily designed for performance monitoring and display trends amongst population interacting with children' social. Therefore, the use of population level data to individual cases as in machine learning maybe subject to debate, urging the need to account for data quality and contextual aspects as part of the design itself. To deal with this challenge, IBM proposes to use cognitive computing features in IBM's Watson as a tool to learn and delimit the boundaries of resources used in child welfare system as highlighted in Stewart of Change Institute report on Child Welfare Practices (Day et al., 2016).

5.3.3. *Prospect of explainable AI*

The recent Alain Turing Institute's report on Ethics review of machine learning in children's social care raised the prospect of explainable-AI (Samek et al., 2017) technology as prominent recipe to tackle the growing concern of use of AI in governance and CSC field. Especially, it is expected that endowing AI tools with capacity to explain their outcome through visualization schemes, approximation with linear and classical tools, model distillation, among others, provide efficient tool to ease acceptance of the technology by the various stakeholder involved. This enables the caseworker to trace back the rationale behind the risk score provided by the AI-based predictor tool for instance, and thereby, may initiate a corrective action whenever needed. It is also that through its advanced visualization toolkit, explainable AI offers useful opportunity to stakeholder to engage in the decision-making process by tracking the various intermediate stages of the decision-making process.

5.3.4. *New conceptual framework*

In light of the aforementioned discussion and attempting to establish a link with the initial conceptual framework provided in Fig. 2, it is worth questioning whether an updated version can be put forward in the light of the new encapsulated knowledge from analysis of current AI initiatives and literature review. Fig. 8 draws a high-level description of a potential AI-CSC governance framework accordingly. The proposal inherits (Wirtz et al., 2019) generic AI-governance framework that distinguishes AI-technology layer, AI-ethics layer and AI-regulatory, while accommodating the context of CSC field by emphasizing the Ethics chart of child welfare. On the other hand, the proposal distinguishes the implementation layer that is based on co-development and pilot projects alongside the various CSC stakeholders. Finally, a set of enablers are distinguished, with a special highlight on AI-explainable tools that can link both Ethics layer, Technology layer and Implementation layers.

5.3.5. *Alternative frameworks*

Trencher (2019) promoted the “Smart City 2.0” as a decentralized user-centric where smart technologies, including AI, are used as a tool to handle social issues. In this framework, AI-technology enablers potentially employed in CSC-governance are expected to benefit from the

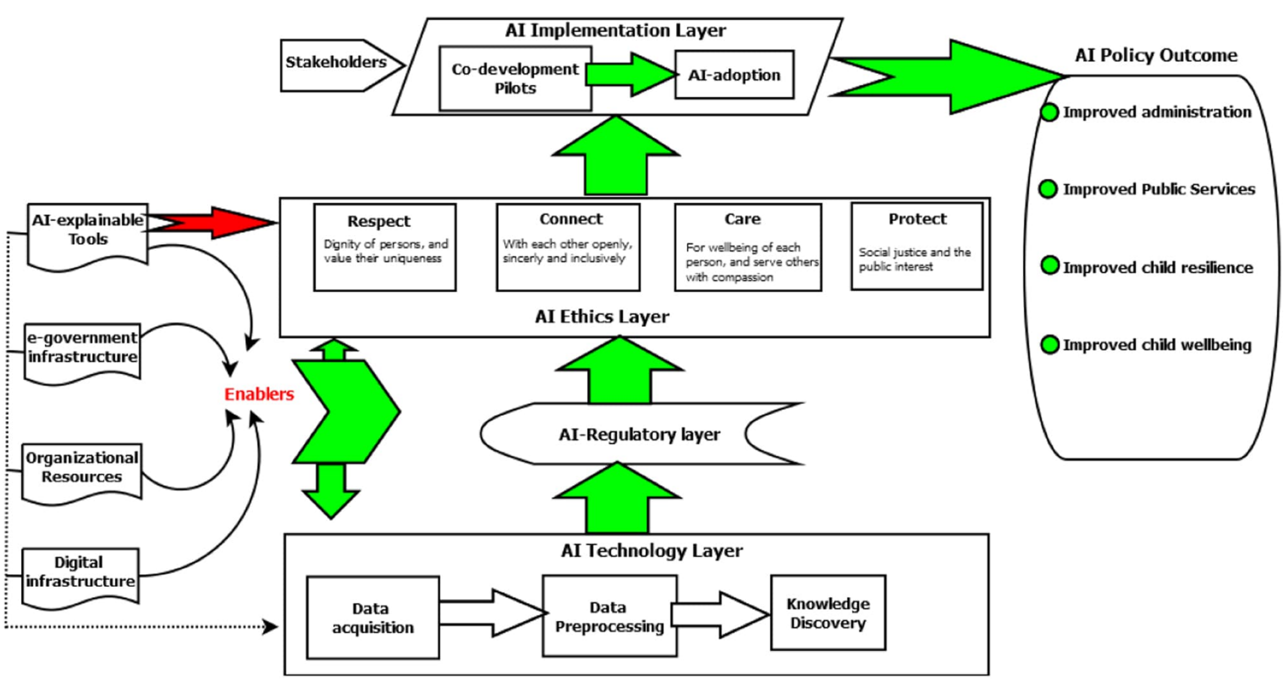

Fig. 8. Conceptual framework for AI-CSC-governance.

overall smart city ecosystem that would ultimately identify appropriate AI technology that would ensure sustainability, growth and positive social change. Nevertheless, although smart city 2.0 is primarily focused on citizen needs and measures that enhance effective governance, there is a lack of empirical studies with a focus on CSC field. Trencher's study targeted Aizuwakamatsu smart city in Fukushima in Japan using a set of interview-based data regarding the quality of the provided services and governance.

Fursov and Linton (2022) suggested the idea of Producer-User Social Innovation (PUSI) model distinguishing innovation that occurs in economic environment and that occurring in non-market environment. It assumes that social innovation occurs as a combination of product and user innovation. Projecting PUSI onto CSC-governance can be viewed from different perspectives. For instance, the CSC-governance can be seen as an aggregation of several subtasks where each task involves both AI-related tool associated with the increased digitilization and user innovation pertaining the training and interaction required to utilize these tools. Likewise to Smart City 2.0, framework, PUSI model lacks evidence that testifies its soundness to CSC field due to sparsity of cases involved in CSC and practical differences from one agency to another one.

"Big data and analytics" offers interesting insights to devise appropriate recommender systems that would provide useful aid to users involved in CSC-governance. Although, such ideas have been widely employed in healthcare where clinicians were offered non-binding suggestions from various health-recommender systems that employ various sources of information (Weerasinghe et al., 2022, Rostami et al., 2022a, Rostami et al., 2022b, Rostami and Oussalah, 2022). Nevertheless, it should be noted that as already pointed out in the discussion part of this paper, this approach, although interesting, is still challenged by the extent to which the outcome of the recommender system (s) is (are) trusted by users involved in CSC governance.

Other directions can be inspired by Mariello (2007)'s four-stage innovation process: i) discovery and generation of new ideas, ii) screening of these ideas, iii) experimentation of selected ideas, and iv) development of the final selected idea and commercialization. In their review paper, Truong and Papagiannidis (2022) found that AI cannot genuinely generate new ideas, although it can offer useful assistance to innovators across the four stages of the innovation process. In the context of CSC-governance, this suggests that each application of the AI enabled technology potentially involved in CSC-governance would be decomposed into four stage and appropriate explanation should be sought at each stage. Although such direction has its root in Mariello (2007)'s framework of innovation stage, it should be noted that the four-stage innovation model has been primarily developed for business related innovation. Therefore, the extension of this process to non-business related innovation is still to be demonstrated.

Finally, to recap the key findings related to the research questions set up in the introduction part of this paper, Table 5 summarizes the main knowledge gaps and future plan for each research question. For this purpose, we relied on our manual scrutinization of the 161 governance studies together with gaps already pointed out in this literature. These are mainly rooted back to the multi-disciplinary field of AI-CSC-governance and emergence theories in child welfare data analytics as well as the prospects of use of AI-explainable tools in the field, which have not been fully explored in the AI-CSC-governance literature.

6. Conclusions

The development of AI technology, alongside the datafication of the society and the multiplication of e-government initiatives, is nowadays recognized as a cornerstone principle in many national and European development policy documents due to its ability to sustain growth and achieve citizen wellbeing. This paper reviewed the use of AI-technology in governance of Child Social Care (CSC) emphasizing aspects of resilience and child wellbeing. The paper attempts to review the state of

Table 5
Review of Gaps and future research agenda.

Research question	Gap in literature	Possible Future Research Agenda
Q1	G1: Dynamic child resilience-wellbeing relationship G2: Impact of organizational resilience on individual, family resilience G3: Scope of AI in guiding organizational resilience G4: Impact of education resilience on organizational resilience	-How to take into account the fact that child resilience traits and wellbeing are not stable? -How to refine the existing assessment metrics accordingly? -How to use conditional reasoning when assuming that such measure become stable when conditioned on another event? -How do current organizational resilience models compare with system reliability and dependability in system theory? - How do these organizational resilience models view from human-machine system in complex system theory? - How symmetric /asymmetric is the relationship between individual, family units and organizational resilience? -What is relationship between absorptive, transformative resilience and individual, family and organizational resilience? -How can expert system like approach be used to derive inputs to organizational resilience model? - What existing AI-explainable tools be used in the design of organizational resilience model? - How to assess the short, medium and long term impacts of the use AI technology on social worker daily practice? -What is the maturity level of AI technology that would boost the implementation of AI based governance in CSC? -How do prominent education resilience models map to organizational resilience? - How can AI contribute to boost and interlink education and organizational resilience?
Q2	G5: Discrepancy and fragmentation of knowledge among distinct stakeholders. G6: Impact of AI explainable tools G7: Use of AI explainable models for resilience evaluation	-How to deal with the sparsity and discrepancy of data issued from distinct sources and agencies in the design of the AI technology? -How to integrate contextual factors in a concise and a coherent manner during the AI development process? - How to assess and delimit the boundaries of such data quality in a typical CSC application, e.g., child neglect or maltreatment? -How will AI-explainability impact the development of AI-ecosystem through embedded visualization and interaction tools? - How will AI-explainability leverage the performance and interpretability /transparency of the underlined AI-governance? - How will the CSC caseworker interact with various modalities offered by AI-explainable tools in short, medium and long term? - What is the current of technology maturity levels for developing efficient pilot CSC AI-governance

(*continued on next page*)

Table 5 (*continued*)

Research question	Gap in literature	Possible Future Research Agenda
		case studies? -How will the new interaction modalities of AI-explainable tools be integrated in risk assessment models? - How will the above risk assessments be linked to child / family and organizational resilience? - How to leverage performance and explainability of these risk assessment tools?
Q3	G8: Relevant assessment metrics G9: Business and investment model	-How to identify relevant and coherent performance metrics that enable efficient comparison of AI-initiatives? - How to perform qualitative and quantitative evaluation accordingly? - How can organization detect bias in emerging decision-making? -What is the return in investment in such AI-initiative projects and how to sustain such investment?

knowledge in this field, first within public management discipline and, second, at wide, by performing a systematic literature review following PRISMA methodological framework, and, finally, by reviewing some of popular AI-initiatives reported by AI-Watch or EU / US AI reports. The finding from the first investigation has led to the development of a conceptual model for AI CSC governance according in public management discipline highlighting the interlink between individual, community and governance levels in achieving CSC targets in terms of child resilience and wellbeing, and the contribution of AI technology. The systematic review identified a total of 440 relevant articles, which are then scrutinized in terms of their relevance to individual, family, community and governance like contributions. Categorization and identification of key AI methods employed at each level have been examined and discussed. Likewise, the identified AI-initiatives have been examined in terms of the scope of the underlined AI-governance employed as well as inherent limitations. The findings have been exhaustively commented and scrutinized in terms of the nature of AI-approach employed, performance achievement, implementation stages, ethical aspects and societal adoption. The findings testify on the sparsity of research in this field, especially given the CSC conservatism where child neglect and maltreatments are often subject to media influence and political agenda. Interestingly, a conceptual framework has been put forward which interlinks AI-Technological layer, AI-Ethics layer, AI-Regulatory layer and AI-Implementation layer. The framework explores the potential of co-development through a set of pilot projects with active involvement of CSC stakeholders to speed up the implementation, as well as the importance of enabling factors, with a special focus on the yet to be explored AI-explainable tools. Finally, the paper lies down foundations for future research agenda in CSC AI-based governance that are intensively highlighted.

6.1. Practical and social implications

The concepts of resilience and wellbeing investigated in this paper have useful practical implication in education where empowering student with resilience and wellbeing can help student to strengthen his learning capabilities and emotional skills. Similarly, the concept of community resilience and wellbeing have direct impact to to several sociology fields such as minority integration, migration crisis handling, and business collaboration, among others.

As claimed by the UNICEF AI children report, the introduction of AI tools becomes a pre-requisite for fulfilment of child's wellbeing in this digital era as one cannot exclude the child benefiting from advanced gaming and robot-based AI products. However, a balance should be found to mitigate risk of technological harm and social exclusion. This balance requirement should be translated to design constraints and further technological development by manufacturers and service developers.

The conceptual model highlighted in this paper bears several overlapping with governance theories that are currently implemented in practice, which can promote its social impact. For instance, democratic and legal governance theories are in full agreement with the concept of co-development pilots, active stakeholder participation and transparency requirement brought by AI-ethics layer. Similarly, network governance theory is straightforwardly embedded in 'connect' module of the AI ethics layer.

The interactive aspect in the conceptual framework opens up the question of the extent to which the outcome of AI-tools will be enforced in the decision-making process where a prudent attitude between a fully automated and aid-to-decision like tools should be sought.

Funding acknowledgment

This work is partly supported by Finland Itla Children's Foundation (Itsenäisyyden juhlavuoden lastensäätiö), which is gratefully acknowledged.

Authors' contribution

XW and MO conceptualized and designed the study, interpreted results, drafted the initial manuscript. MK, TR and PV reviewed and revised the manuscript and assisted in analysis aspects. All authors read and approved the final version of the manuscript and agreed to be personally accountable for all aspects of the work.

Declaration of Competing Interest

The authors declare no conflict of interest of any kinds.

Acknowledgements

This work is partly supported by ITLA foundation for Equal Wellbeing for Children and Families, EU YoungRes project (#823701), and Academy of Finland project DigiHealth (#326291), which are gratefully acknowledged.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.joitmc.2023.100157.

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