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Impact of artificial intelligence on resilience: Contributions, challenges, and opportunities

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Abstract

Traditional methods of creating psychological, social, and system resilience are barely adequate for the magnitude and complexity of contemporary threats. This paper studies recent advances in Artificial Intelligence (AI)-based resilience research, including major contributions and current challenges and opportunities. A systematic review was carried out under PRISMA guidelines until 2025 from different databases, including Scopus and Web of Science. After reviewing more than 760 records, we included 176 relevant studies from psychology, public health, climate adaptation, infrastructure and other disciplines. The results illustrate that AI's development supports resilience by improved mental health and psychological well-being through AI-enabled interventions, enhanced healthcare and epidemic preparedness with predictive analytics, strengthened climate preparedness and disaster response from early warning systems to resource optimization, greater resiliency of supply chains, energy grids and other critical infrastructure through intelligent automation and decision support. However, a number of limitations were found, despite these improvements. Issues of privacy, bias, and reliability as well as the requirement for human supervision and ethical governance continue to pose barriers to the holistic development of AI powered resilience technologies. We argue in our analysis that AI can be utilized as tool for enhancing resilience at the macro level (policy makers) if used in proper, just manners. We end with recommendations on how to address the current shortcomings, including increased AI transparency, inclusivity and inter-disciplinary collaboration that might enable us to harness the power of AI as a game change for a more resilient and sustainable world.

Keywords: Resilience, Artificial intelligence, Machine learning, Sustainability, Decision making, Sustainable development.

1. Introduction

Throughout the whole world even today we are still dealing with complex entwined while exceptions of challenges that stretch us as humans, ecologies and systems. The COVID-19 pandemic has exposed disparities in our health care systems, mental health services and supply chains, but it is also a catalyst for digital transformation unlike any we have ever seen. At the same time, natural disasters are becoming more frequent and severe due to climate change impacting the stability of ecosystems, food security and community livelihoods [1-3]. These concurrent crises disproportionately impact marginalized populations, such as children, adolescents, older adults and vulnerable communities impairing the psychological reserve that promotes resilience. Resilience, as the active ability to anticipate, absorb, accommodate or recover from disturbance is increasingly being acknowledged as a crucial aspect in understanding survival and thriving under various conditions [3]. Psychological resilience may assist people in remaining well and happy despite adversity and stress, factoring in areas such as social support, self-efficacy, emotion regulation and coping. Societal agency resilience is more than individual psychology and involves more complex systems, for example health organizations with the governance of pandemics, ecosystems by adapting to climate change or supply chains by absorbing a disruption. The traditional ways of assessing and improving resilience, however, frequently include retrospective analysis static risk assessments, and linear models for intervention that fail to account for the complexity, uncertainty and fast dynamic faced in contemporary crises.

Artificial Intelligence (AI) is increasingly being seen as a disruptive enabler and driver with wide-ranging implications for resilience in all of these areas [2,4,5]. Machine learning algorithms can be used to comb through large datasets and find patterns that humans cannot, which makes it possible to predict psychological distress, disease outbreaks, climate change impact and system vulnerabilities [6-8]. Real-time monitoring of mental health is also made possible through Natural Language Processing (NLP) on social networks, and automatic screening tools [3]. Computer vision helps in disaster response using satellite image analysis and infrastructure damage measurement. Optimization routines help in resource allocation in health care systems, energy microgrids and supply chain networks. Deep learning models promote personalized interventions for depression, anxiety, Post-Traumatic Stress Disorder (PTSD) and burnout by considering individual-based features, environmental factors and treatment outcomes.

The incorporation of AI into resilience models has the potential to add entirely new dimensions of proactive as opposed to reactive action [9,10]. Predictive analytics make it possible to detect those at risk for psychological distress early enough for interventions to be made before a tipping point is reached. AI-powered decision support systems could assist health care facility workers in balancing surge capacity during pandemics while sustaining them based on optimal scheduling and allocation of resources. Machine learning models have been very useful for climate adaptation, it's possible to predict more clearly in a variety of dimensions including patterns of drought, and flood risk or change in ecosystem that leads decision making by adaptive management [11-13]. In cybersecurity, resilience is strengthened by AI systems that are capable of autonomously identifying network anomalies and potential breaches in the moment. It is one of the most common AI use cases in supply chain where machines learn about demand and develop a shortage and recovery strategy, thereby enhancing the organization’s ability to withstand disruptions. Notably interesting domains for AI and mental health to meet are the psychological. Machine learning predicting resiliency trajectories from datasets, such as the Connor-Davidson Resilience scale and psychological resilience scale, identifying protective factors within various population subgroups. AI-enabled digital therapeutics offer personalized mindfulness-based interventions, Cognitive Behavioral Therapy (CBT), and emotion regulation training outside of its conventional clinical context. Chatbots and virtual humans offer social support and psychoeducation to fill these gaps in mental health service provision, which is especially acute for students, youth, and marginalized communities. Longitudinal studies and cohort information provide an opportunity to identify trajectories of development, as well as windows of opportunity for interventions designed to enhance resilience across infancy through aging.

Healthcare systems are complex adaptive systems, and AI plays a role in operational resiliency in both normal operations and crisis management [2,14-17]. Predictive dashboards forecast patient loads, balance bed distribution and oversee pharmaceutical supply chains. While the use of AI was widespread during the COVID-19 pandemic, applications included SARS-CoV-2 detection and contact tracing, vaccine distribution planning, and public health communication [9,18-21]. AI-enabled clinical decision support enables nurses and other healthcare workers to conserve mental bandwidth as they provide care. However, deployment concerns are interoperability with existing health information systems and support for human intervention in decisions that would affect patient safety and wellness.

Environmental and ecosystem resilience now more than ever relies on AI’s ability to monitor biodiversity, evaluate habitat susceptibility and inform conservationists [22,23]. Machine learning studies sensor networks, satellite images and field data to monitor shifts of ecosystems over time, forecast tipping points and assess interventions for restoration. AI-enhanced climate models increase the precision of projected temperature trends, rainfall distribution and extreme weather events, all critical for urban planning, agricultural adaptation planning and disaster risk reduction [24-26]. AI employed for microgrid management to enhance renewable integration. Gets the voltaic to the systems while maintaining grid stability during outage. Infrastructure AI can be utilized to monitor, predict maintenance periods and disaster response of transportation, communication and utility infrastructures. Computer vision monitors the structural health of bridges, buildings and essential infrastructure, allowing for preemptive maintenance that prevents catastrophic failure. Artificial intelligence manages traffic flow during evacuations, orchestrates emergency services in disasters and prioritizes restoration after disruptions. Machine learning is applied to electric power distribution systems for load prediction, fault detection and self-healing grid structures minimizing outage effects. Smart city programs involve several AI systems for comprehensive urban resilience including transportation, energy, water and communication networks.

Measures of social and community resilience include components such as leadership, social cohesion, innovation potential, and adaptive governance arrangements [27,28]. AI provides by the social network analysis that identifies community vulnerability and strength, sentiment analysis that informs public communication strategies, and participatory platforms enabling collective decision-making. Educational systems use AI for personal learning that supports cognitive resilience and meets the specific needs of students when school is disrupted and instruction moves from in-school to out-of-school. Economic resilience from AI-driven forecasting, risk management and adaptive resource allocation to help organisations and individuals draw through uncertainty [19,29-31]. Despite increasing attention towards the use of AI for resilience, a number of knowledge gaps remain. First, existing reviews tend to concentrate on individual domains e.g. mental health or disaster management, neglecting broad synthesis across psychological, healthcare, environmental and infrastructural resilience. Second, few critical studies explore the ways in which AI might reinforce some resilience dimensions while undermining others e.g., enhancing efficiency while decreasing adaptive flexibility. Third, with the fast evolution of AI, recent progresses on explainable AI, federated learning and edge computing are largely underexplored in the context of resilience analysis.

This enlightened literature review attempts to fill this gap through three fundamental purposes. Firstly, we describe patterns and relationships across a broad range of AI applications that can be organised into five domains, namely, psychological, health care services, environment, infrastructure and social to systematically synthesise current knowledge about how AI is enhancing resilience. Second, to undertake a critical examination of challenges, risks and limitations that derive from the use of AI-augmented resilience approaches such as technical limitations, ethical dilemmas and equity issues. Third, identify promising new opportunities and potential future directions that take advantage of AI to also minimize risks and support an inclusive, sustainable, and human-centered approach to strengthening resilience.

This review makes several contributions to the field. It creates the first integrated, trans-disciplinary synthesis of AI effects on resilience, which enables comparability, knowledge transfer and achievement of generalisable principles beyond contexts. The balanced view to contributions and challenges is a necessary contribution to research, practice, and policy so that informed decisions can be made. By integrating evidence of the effectiveness among cross-sectional studies, longitudinal studies, randomized controlled trials, cohort analyses and key clinical studies, the review builds robust grounds for empirically based practice.

2. Methodology

This comprehensive review of literature followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) approach to facilitate a systematic, thorough, transparent and reproducible process of identifying, screening and synthesizing relevant research investigating artificial intelligence effects on resilience across domains. The review procedure involved three main steps: identification, screening and inclusion, using specific selection criteria and steps for progressively limiting the pool of literature to studies that were most useful in fulfilling these research aims.

The first identification process involved extensive searches in academic databases and registers to encompass the span of interdisciplinary research on AI and resilience. Database searches resulted in 768 records sourced from peer-reviewed journal articles, conference proceedings and technical reports across a wide breadth of psychology, computer science, health care, environmental science engineering and social sciences. There were a further 26 references found from other sources such as clinical trials databases, systematic review repositories and grey literature. Records had deduplication and initial eligibility assessment prior to screening. There were 212 entries of duplicate reports and these were deleted with automatic bibliographical program help in combination with manual check of article identity the same study by multiple database suppliers. Thirteen records were flagged as not suitable by automation due to predefined reasons such as publication language limitations, document types and basic relevance criteria. A further 5 articles were excluded for other reasons, being for retracted articles (n=4), as the full text was not retrievable despite our attempt to obtain it (n=1) and studies outside of the temporal range specified by eligibility criteria. We excluded records, and 564 unique records went on to formal screening.

The screening process included the systematic consideration of titles and abstracts against agreed-upon inclusion and exclusion criteria, which were established according to the review objectives. Each of the 564 records was evaluated by two independent reviewers and discrepancies were resolved through discussion or by third review if required. Inclusion criteria included the relevance to AI technologies such as machine learning, natural language processing, computer vision, or predictive analytics, explicit attention to resilience constructs e.g., psychological resilience, system resilience, and a threshold for methodological quality and detail that would enable assessment of quality. Following the initial screening, 173 documents were excluded driven by insufficient emphasis on AI technologies or resilience outcomes, lack of empirical or systematic analysis data, and serious methodological limitations precluding any interpretation. The latter 391 studies were further considered as possibly related and retrieved in full text. All 374 identified reports were subjected to detailed full-text screening to decide on eligibility. We have independently evaluated each report using specific inclusion criteria that included relevance of the study design, description of AI clarity, valid resilience measurement/assessment and quality of reporting. Reports were excluded for three main reasons: 88 reports had insufficient detail about AI approaches or processes such that contributions and limitations could not be assessed; 46 reported on technology applications with no clear emphasis on resilience or they did not measure outcomes specifically addressing constructs of resilience; and 43 had insufficient methodological rigor in terms of sample size, measurement instruments, or analytic approach.

After strict selection and eligibility that 176 studies were included in ensure meeting the all inclusion criteria. Together these studies provided 197 reports, as there were multiple papers from one study with different focus populations or points in time. The types of articles in the included studies covered cross-sectional study, longitudinal study, cohort analysis, Randomized Controlled Trial (RCT), large-scale clinical trial, systematic analysis and human experiment. Such methodological variety allowed for the index and full synthesis of diverse types of evidence. Fig. 1. shows the framework for eligibility criteria based on PRISMA Protocol.

3. Results and discussions

Co-occurrence analysis of the keywords in literature

The co-occurrence map (Fig. 2) displays a dense, interconnected core in which “artificial intelligence” and “resilience” connected with “decision making,” “risk assessment”, and “machine learning”. The co-occurrence map positions “artificial intelligence” and “resilience” as twin anchors, suggesting not only that research sees AI less as stand-alone technology but also as the connective tissue across resilience problem settings. The ‘decision making’ and ‘risk assessment,’ which lie near the center and connect technical methods to application areas, that the linkages are most powerful. Repeated references to “uncertainty” imply that the field conceives of resilience as coping with volatility rather than simply restoring normalcy, and the value in AI-based analysis is framed in terms of turning data and models into timely, defensible decisions. Another major application vein includes “climate change,” “natural disasters,” “floods” and “disaster prevention,” attaching to the main route through the concept of a decision support system', ‘smart city’, and IoT’. This pattern illustrates how themes about environmental and urban risk are converging along data-enabled monitoring and response. The prevalence of edges is also a hint that in the studies hazards are rarely dealt with singularly, and there is often sensory information processed together in one solution with prediction such as, how to orchestrate route, coalesce or prioritize resources when conditions change.

Another closely connected cluster groups “sustainable development,” “sustainability,” “big data,” “data analytics,” “information systems,” “supply chain” and “blockchain.” In this context, AI emerges as a tool for supply chain view, disruption propagation analysis and traceability in complex networks. The fact that “information management” comes so close points to the possibility that resilience is not only about modelling shocks, but also controlling the flow of data, access and data provenance among stakeholders. From a socioeconomical to sociotechnological side, a green cluster around “human”, “adaptability”, “innovation”, “technology” “education” and “student”; including with “robotic” and “automation” has global challenges in undermining the organizational learning dimension and human capital of resilience. Works in this connection focus on how AI-enabled systems work when coupled with training, new work practices and human-in-the-loop designs. That the pandemic node has links to decision support and digital will indicate how acute crises have advanced digital adoption, and with it investigations into resilient operations.

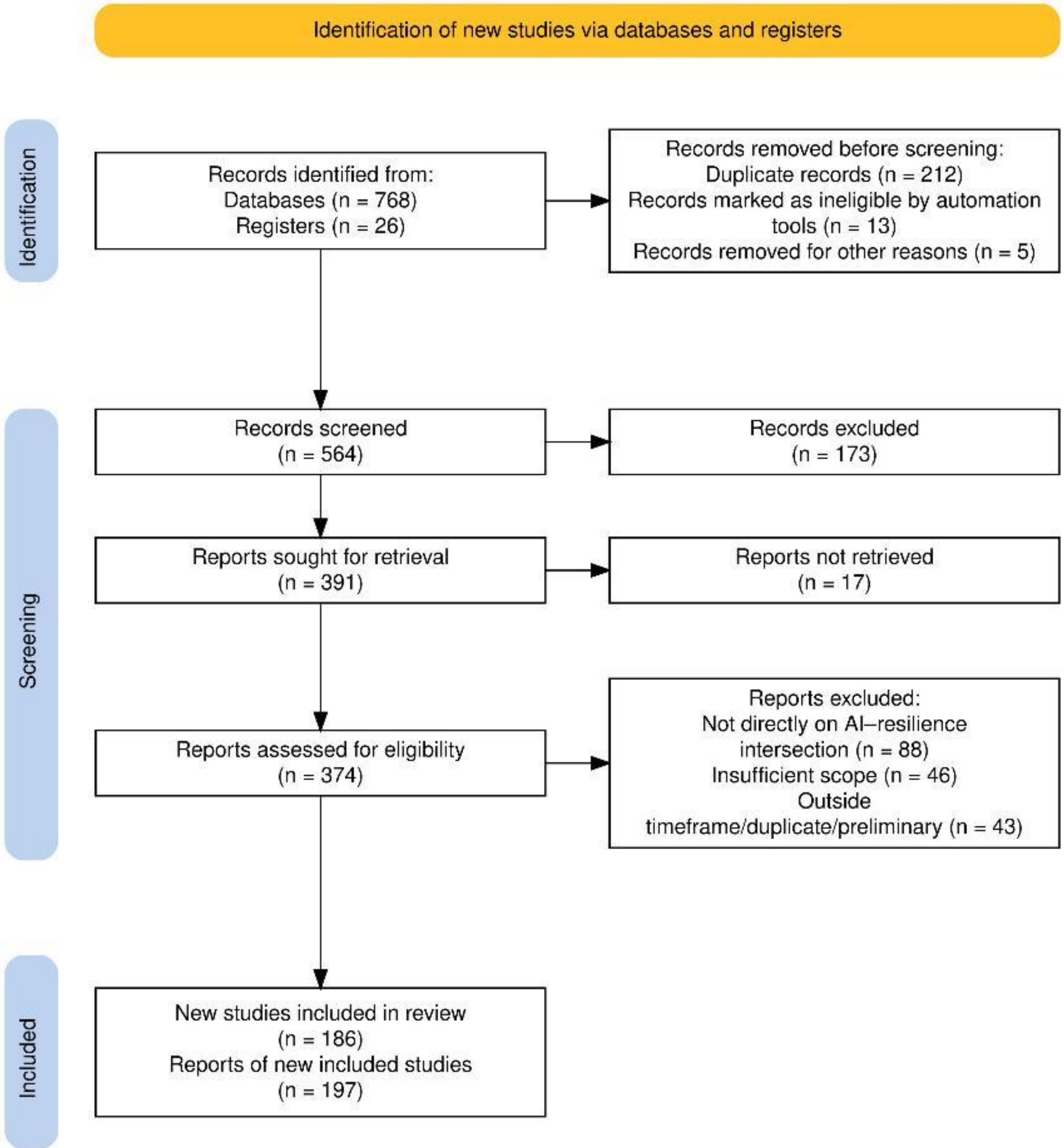

Fig. 1. Framework for eligibility criteria based on PRISMA Protocol

The methodology with machine-learning neural networks, learning systems, reinforcement learning, forecasting and optimization a technique-centered belt connected to a relation like reliability, recovery or system resilience. This illustrates a pipeline from prediction to prescription, models predict modes of failure, and optimization/reinforcement learning search for resilient recovery strategies under constraints. The relations to “economics” and “power” indicate cost and energy or infrastructure performance are often considered common objective functions in resilience formulations. Another purple cluster with “cybersecurity,” “cyber security,” “cyber-attacks,” “cyber-physical systems,” “critical infrastructure” and safety also indicate a different, but neighboring discourse. The edges that connect this cluster with “critical infrastructure,” “reliability” and “risk assessment” indicate a security-centric understanding of resilience, in which AI is deployed to detect threats, characterize abnormal behavior and contain as fast as possible. When contrasting the climate-and-disaster cluster with the cyber cluster, we observe that cyber seems to present lower internal diversity in need of further integration with physical-hazard models to support integrated risk assessment and multi-hazard planning.

The “IoT,” “smart city,” and “cyber-physical systems” nodes act are the bridge between environmental resilience and cybersecurity in the sense that digitalizing infrastructure increases capability, but also attack surface. Their strong connections to “neural network”, “decision making”, and “safety” suggest that the edge intelligence and real-time control may be the next frontier. Digital twins inherently occupy this meeting place that of simulation led risk assessment, which combines physical sensing with cyber defense. Terminological reduplication e.g., “cybersecurity” and “cyber security,” or, as an additional to the primary node of interest artificial intelligence suggests that this corpus files articles under several indexing conventions. If the keywords were normalized, it would probably tighten up the core and bump up some of those bridging words since many are behaving like hubs.

The contributions, challenges and trends reveal a network that lays the foundation for practical contributions such as predictive and prescriptive analytics for risk and recovery, AI embedded in smart connected infrastructures, decision support based on data. Second, it presents long term problems such as how to handle uncertainty in non-stationary environments, safety of learning systems (including reliability), organizational level issues related to the quality and governance of data or keeping humans in the loop. At the end of the day, the sustainability versus cybersecurity community divide is a coordination problem with technical, institutional and regulatory dimensions. By combining cyber-physical threats models with climate and disaster simulations utilities and cities could to have access to a multi-hazard resilience planning tool. Modeling operations research, domain constraints and reinforcement learning together should give way to more prudent policies for repair, crew dispatch and supply chain rerouting. And perpetuating the human-centric lineage, learning, agility and innovation with methodological development in AI for designing interpretable/auditable AI supporting social resilience rather than just engineering optimality.

At some level, artificial intelligence in the world by resilience review by domains is the catalytic layer that hybridizes computer thinking with human-ecology-infrastructure. The outcomes illustrate that AI automation at several layers of resilience augmented with predictive analytics, adaptive response in real-time, tailored intervention progams, and systems way deep optimization drastically enhance the potential to adapt even the psychological level up through social, environmental and infrastructure levels. As AI is integrated within resilience models, novel approaches to managing adversity can be realized, which are future-oriented rather than reactive. Machine learning was much more fruitful in extracting vulnerability pattern s, predicting their crisis trajectories, optimum allocation of resources etc. of critical events. From mental health care systems identifying early warning signs of psyche distress to climate resilience systems that measure ecosystem vulnerability, AI applications are ushering us toward previously uncharted terrains of knowing and resilience in the world. But those advancements also bring thorny issues of equity, access, algorithmic bias and data privacy and even potential threats to health from technology use.Fig.3 shows the impact of artificial intelligence on resilience. First, the human side. Research on human covers a broad range of human participants across gender, female and male groups, and the life course, child, adolescent and adolescents, young adult, adult, middle-aged, aged, and aging populations. These groups differ in their experiences of stress, and this difference is why the studies closely monitor vulnerability and protective factors such as social support, mindfulness, and physical activity. The family settings, caregiver roles, parents, and the child-parent relation matter as well but only during trauma, disaster, and the pandemic disruption. Students and the broader student population experience learning and performance pressures, and they are typically measured for stress via self-report tools; specifically tailored digital supports them to pace study, manage emotion, and boost self-efficacy and self-concept. The community context, religion, local culture, and urban area services design also influence how people seek help, follow guidance, and reconstruct after a shock. Mental health is an important outcome. The diagram emphasizes psychology and mental health terms like anxiety, depression, anxiety disorder, posttraumatic stress disorder, and distress syndrome, which coexist with larger dimensions like wellbeing, well-being, psychological well-being, and quality of life. Stress is monitored in various ways, namely stress, mental stress, psychological stress, and even physiological stress, because the strain was expressed as feelings, thoughts, and body experiences. The skills that underpin resilience are monitored as well and include coping, coping behavior, emotion regulation, and the psychological adjustment, the relevant processes are those of adaptation, clinical and psychological. These strengths are enhanced by AI tools through early screening, simple prompts for digital therapy, and Just-in-time coaching to lower the exposure to the risk factors and support everyday levels of decision making.

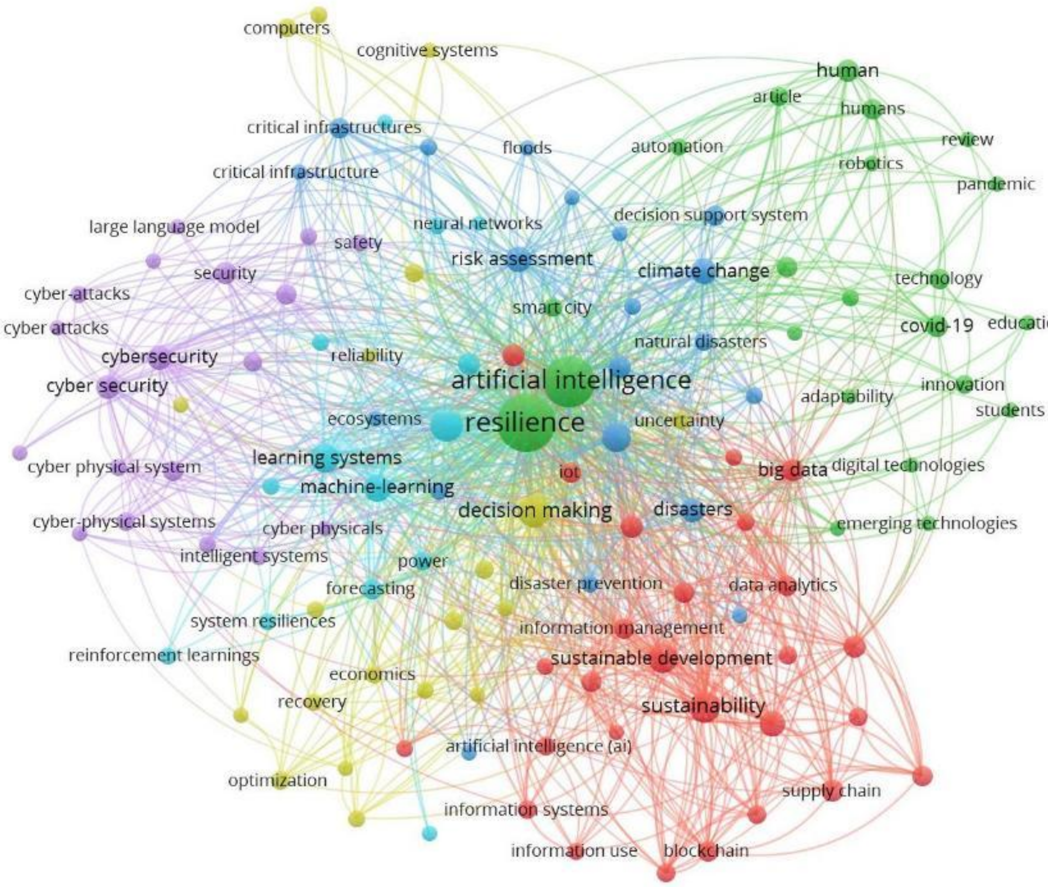

Fig. 2 Co-occurrence analysis of the keywords in literature

To assess psychological resilience research often use the Connor Davidson resilience scale on top of the broader psychological resilience scale. These are typically delivered with Likert Scale items and conscientious psychometry to check reliability and impartiality. Since mental states also have a physical footprint, some studies include sensor-based indicators of physiology and metabolism to capture stress responses more directly. Major clinical study and clinical article formats share exact findings and follow up time points allow authors to track prevalence shifts and long-term recovery. Holistically, these choices keep the evidence base handy and reliable. The diagram also shows how different study types provide complementary insights. Cross-sectional studies show a snapshot of what is happening right now.

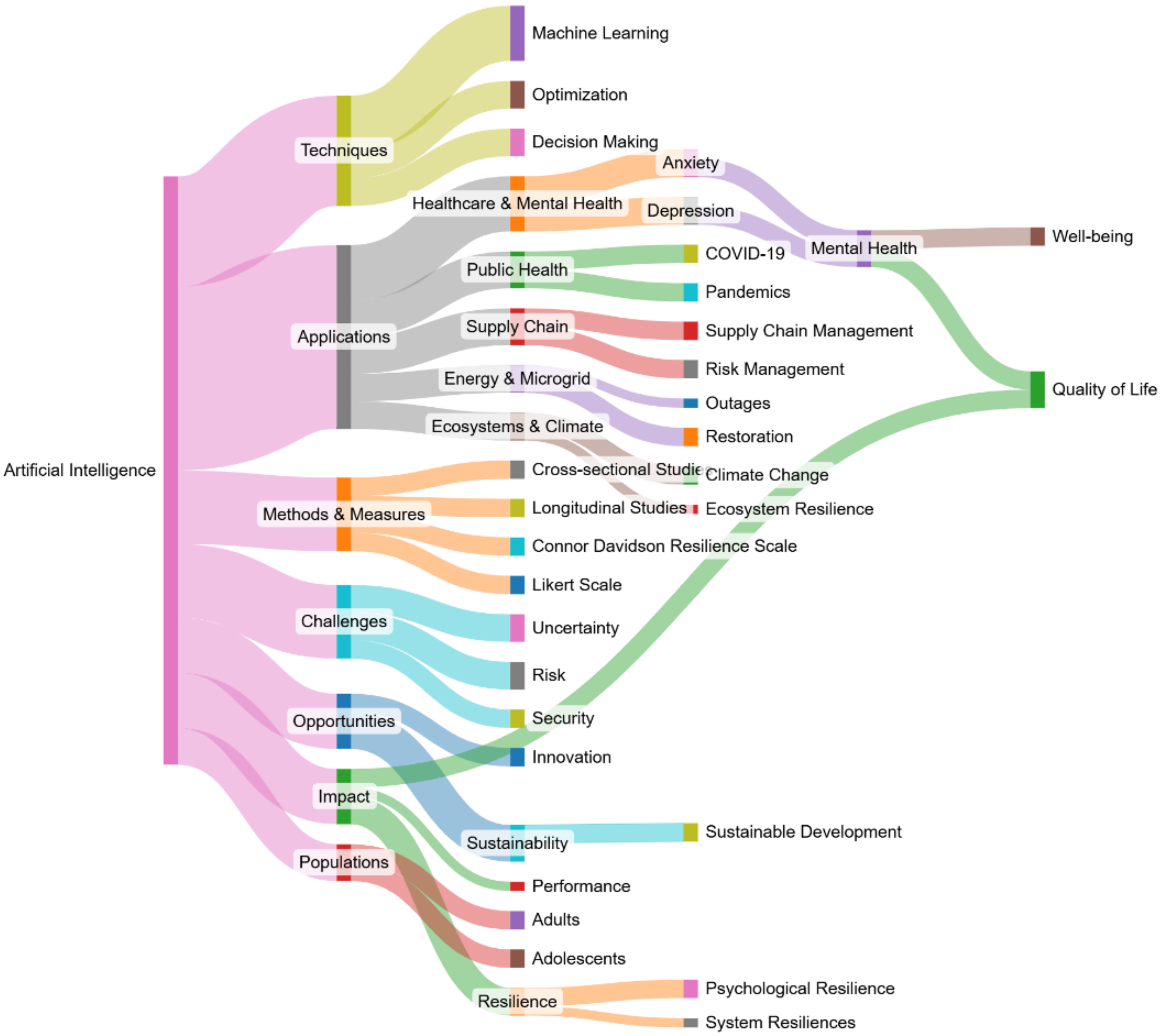

Fig. 3 Impact of artificial intelligence on resilience

Supply chains make up a third stream. AI makes supply chain and supply chains more robust by, among other things, predicting demand swings, rerouting around bottlenecks, reducing waste, and maintaining service at tolerable levels. These become the new de facto working laws in supply chain management. They also integrate directly into risk management structures, which recognize risk and uncertainty as standard components of contemporary logistics. However, security, network security, and cybersecurity issues must be addressed during system solidification in order to prevent digital tools from taking on new deficiencies. The ultimate objective is for these solidified systems to develop a collection of system resilience, which include both resistance to immediate shocks as well as recovery to restore the chain when portions fail. The systems image is completed by environmental and ecological resilience. AI is used to map habitat alterations, safeguard biodiversity, and strengthen ecosystem resilience through efforts to improve ecosystem and ecosystems health. Table 1 shows an AI applications, techniques, and methods across resilience domains.

The techniques branch shows up in machine learning, which identifies patterns in texts, images, and sensor streams and then converts them to useful predictions. Optimizations allocate scarce resources, such as medical people, medical supplies, or repair crews. Integer programming drives many such allocations when the choices are literally yes-or-no, as in which line to fix first after an outage. Stochastic systems account for the randomness of weather, demand, and failures, and uncertainty analysis measures how sure the model actually is. Such estimates feed into the decision-making tools that support the labor at every step. In health and mental health, AI might enable earlier detection and much quicker access to therapy for anxiety, depression, and posttraumatic stress disorder, i.e., a better Quality Of life. Health care personnel and health labor, meaning every nurse and the nurses in the hardest units, may experience decision support, competent scheduling, and clear dashboards due to which burnout and burnout professional would decrease. Better balance boosts performance and opens time for learning and rest. Schools and the universities' most crucial clients, the students, benefit from the models that guide pacing, offer mindfulness or physical activity nudges, and aid the teacher in identifying early warning signals. This usage too should be supported with the education so that the end user can read the outputs wisely and the leadership that solicits the feedback rather than enforcing the blind compliance.

Security and ethics are not optional. AI systems are already at home in hospitals, in grids, in supply chains. That means that cybersecurity and network security have to be part of the design from day one. Policies need to allow room for transparent disclosure about how and where the data comes from, as well as updated models, and for judicious messaging around risk, so that people understand what the system can or cannot safely do. In intimate settings where family life, care-giving or religion becomes an issue, communities would have to be brought in early to customize the tool for local values. Here, the right safeguards preserve trust and increase acceptance. In clinics, the earlier screening and smarter alarming reduces the symptom load and accelerates healing. In Infrastructure, intelligent control equals reduced outages and better-balanced electrical power distribution, even as turbulent times become the new normal. Sophisticated urban planning and disaster management is not only less devastating, but usually means that cities know when floods are coming. In ecosystems, targeted conservation nurtures biodiversity and provides a shield against the worst waves of climate change.

Repetition on future directions is realistic and definitive. It is of interest to continue research that merges design and using RCT evidence where it can be linked to cohort analysis and longitudinal studies produce materially credible results. The measurement should remain robust for both invariants through psychometry checks of reliability and fair use of the Connor Davidson resilience scale, the psychological resilience scale, and Likert scale instruments concerning four gender and age groups. Wherever feasible, data should include physiology and metabolism measures that can be matched with self-report. Methodological work should strive to advance machine learning that is stable in the face of changes in prevalence, clinical practice or climate baselines. On the operations side, optimization, integer programming and stochastic systems will continue to get better at kicking out improved schedules and routing plans for restoration, while also feeding into teams being quick studies of the lessons learned in each event through adaptive management.

Artificial intelligence applications in psychological and mental health resilience

The use of AI in psychological resilience is one of the fastest-growing and transformative human computation intelligence interfacing areas that currently exist [32,33]. With the advent of natural language processing algorithms, we are witnessing a new era in and drastic shifts of mental health assessment and intervention paradigms, where minute-by-minute psychological well-being can be monitored by digital footprints, conversational styles and behavioral cues. Models and methods for deep learning, trained on extensive corpora of clinical encounters, can now detect subtle linguistic markers of depression, anxiety and post-traumatic stress disorder with accuracy that is often as good or even surpassed human clinical judgment [3]. AI-driven mental health chatbots and virtual therapists are now a scalable way of offering instant psychological support, especially useful during the confidence-testing days of COVID-19, when traditional mental-health services have been under enormous pressure. Such conversational agents leverage advanced natural language understanding and sentiment analysis, and context-aware response generation to provide evidence-based clinical interventions such as cognitive behavioral therapy protocols, mindfulness exercises or crisis intervention strategies. The anonymity of and access to AI-facilitated mental health support has been particularly useful in attracting individuals who were traditionally under-served by mainstream mental health infrastructure, such as adolescents, young adults and those located in distant or low-resource areas.

Table 1 AI applications, techniques, and methods across resilience domains

Sr. No.	Resilience Domain	AI Application	Technique/Algorithm	Implementation Method
1	Mental Health Resilience	Depression prediction and early intervention	Recurrent neural networks, LSTM	Continuous monitoring through smartphone sensors and digital interactions
		AI-powered therapeutic chatbots	Natural language processing, transformer models	Conversational agents delivering CBT protocols and crisis support
		Emotion recognition and regulation support	Affective computing, facial expression analysis	Real-time emotional state detection with adaptive coping recommendations
		Burnout prediction in healthcare workers	Ensemble learning, random forests	Workforce analytics combining workload metrics with behavioral indicators
2	Healthcare System Resilience	Resource allocation optimization during pandemics	Reinforcement learning, multi-objective optimization	Dynamic distribution algorithms balancing multiple constraints
		Clinical decision support for emerging diseases	Deep learning, transfer learning	Evidence synthesis from literature and case data for novel conditions
		Supply chain resilience for medical supplies	Demand forecasting, graph neural networks	Predictive inventory management with network vulnerability assessment
		Telemedicine platforms with diagnostic AI	Computer vision, multimodal learning	Remote examination augmentation with automated preliminary diagnosis
3	Climate Resilience	Ecosystem health monitoring	Convolutional neural networks, satellite image analysis	Automated analysis of multispectral remote sensing data
		Biodiversity assessment and tracking	Computer vision, acoustic pattern recognition	Automated species identification from camera traps and audio recordings
		Climate risk prediction and adaptation planning	Machine learning ensembles, spatiotemporal models	High-resolution forecasting of local climate change impacts
		Precision agriculture for crop resilience	Computer vision, reinforcement learning	Real-time crop monitoring with optimized resource allocation
		Drought prediction and water resource management	Time series forecasting, deep learning	Hydrological modeling integrating climate and usage patterns
		Wildfire risk prediction and management	Deep learning, spatiotemporal pattern recognition	Integration of weather, vegetation, and historical fire data
4	Infrastructure Resilience	Power grid fault detection and self-healing	Anomaly detection, reinforcement learning	Real-time sensor analysis with autonomous grid reconfiguration
		Microgrid optimization for energy resilience	Multi-agent reinforcement learning	Distributed energy management balancing generation and storage
		Predictive maintenance for critical infrastructure	Machine learning regression, survival analysis	Sensor data analysis predicting equipment failure timelines
5	Supply Chain Resilience	Demand forecasting and inventory optimization	Deep learning, uncertainty quantification	Real-time demand prediction incorporating external risk factors

		Logistics optimization during disruptions	Combinatorial optimization, reinforcement learning	Dynamic routing and resource allocation adapting to constraints
6	Cybersecurity Resilience	Intrusion detection and threat prediction	Anomaly detection, graph neural networks	Network traffic analysis identifying attack patterns
		Automated incident response and recovery	Autonomous agents, decision trees	Orchestrated security actions isolating threats while maintaining service
7	Social Resilience	Disaster damage assessment	Computer vision, semantic segmentation	Aerial imagery analysis quantifying infrastructure damage
		Emergency response coordination	Multi-agent systems, optimization algorithms	Resource allocation and task assignment among response teams
		Community vulnerability mapping	Machine learning classification, geospatial analysis	Integration of demographic, economic, and infrastructure data
8	Educational Resilience	Personalized adaptive learning platforms	Reinforcement learning, knowledge tracing	Dynamic content and pacing adjustment to individual learner needs
		Student at-risk identification	Classification algorithms, early warning systems	Behavioral and performance analytics flagging struggling students
9	Urban Resilience	Climate adaptation planning and simulation	Agent-based modeling, scenario analysis	Urban system modeling evaluating policy and infrastructure options
10	Food Security Resilience	Crop disease detection and management	Computer vision, transfer learning	Image analysis identifying plant diseases in early stages
11	Pandemic Resilience	Epidemic modeling and forecasting	Compartmental models enhanced with machine learning	Disease spread prediction incorporating mobility and behaviour data
12	Environmental Resilience	Ocean and marine ecosystem monitoring	Deep learning, acoustic analysis	Automated assessment of coral reef health and fish populations

Predictive analytics systems using machine learning may have great promise for early identification of those at risk for psychological distress before they are in crisis. Although monitoring the contents in the EHRs, social media usage, wearable devices use or self-reported assessments trends can help signal early distress levels to be alerted beforehand. AI models have also accurately forecasted during the pandemic susceptibility to depression and anxiety using irregularities in sleep patterns, physical activities, amounts of social contact and linguistic cues through digital communications. The availability of those predictive capabilities changes the game from reactive crisis management to proactive resilience improvement [37-40]. Personalization algorithms Personalized interventions represent a shift in how mental health care is traditionally delivered, providing programs that adapt therapeutic content, timing and mode in response to individual characteristics and preferences and based on responses during use. Such reinforcement learning paradigms provide digital mental health platforms with the capability to automatically update intervention by taking into account user engagement, symptom progress as well as feedback signals. This flexible approach allows the content of resilience-enhancing programmes, and specific skill sets to modulate psychological outcomes (eg depression), age or culture specific issues and comorbid states such as substance misuse. The Connor Davidson Resilience Scale and other validated psychological instruments have been included in AI systems that enable persistent assessment with personalized feedback, effectively transforming resilience enhancement into a closed-loop system.

Affective computing systems to detect and respond to people's emotions, based on the analysis of facial expressions, voice patterns and physiological signals, have expanded further the possibilities available for emotion regulation assistance [41-43]. Such systems can additionally monitor emotional states in real-time and offer direct coping or mindfulness-promoting suggestions, or suggest social support specific to the monitored emotional context. For healthcare workers, students and other groups facing chronic stress or burnout, these sorts of real-time emotional support systems provide an ongoing scaffolding of resilience that develops in the MTurk workers adjusts to your psychology needs. The application of AI in virtual and augmented reality systems has led to engaging healing environments for fostering psychological resilience, via exposure therapies, stress inoculation training or building resilience skills. They enable individuals to rehearse coping strategies in controlled simulated scenarios increasing difficulty, which contribute toward forming adaptive responses prior to engaging with real stressors. For trauma survivors, PTSD sufferers and those who may be preparing for high-stress situations, AI augmented immersive training platforms offer structured pathways to build and enhance resilience.

Artificial intelligence contributions to healthcare system resilience

Artificial intelligence has enabled health systems globally to strengthen operational resiliency which has been well demonstrated during the COVID-19 pandemic as healthcare facilities faced unparalleled demands and stressed institutional adaptive capacity [28,44-47]. Resource allocation algorithms driven by AI helped to ensure the optimal allocation of scarce resources such as ventilators, personal protective equipment, and drugs across healthcare centres with real-time demand prediction, patient flow forecast and regional outbreak scenario analyses. Reductionist machine-learning models fed by epidemiological data, human mobility patterns and social determinants of health allowed healthcare administrators to anticipate surge capacity and strategically deploy resources ahead of a fullfledged crisis. AI-based clinical decision support systems have served as a force multiplier in care delivery, amid overwhelming demand and staff shortages. Deep learning algorithms trained on medical imaging data facilitated fast diagnosis for COVID-19 pneumonia that resulted in faster triage and therapy initiation. Natural Language Processing (NLP) systems used to mine critical insights from unstructured clinical notes, research literature, and treatment guidelines for delivering evidence-based guidance based on the evolving clinical knowledge of new diseases [48,49]. During the crisis, these AI applications served as a force multiplier to our clinicians decreasing burnout while not lowering quality of care.

Healthcare workforce management predictive analytics has tackled sensitivities pertaining to staff burnout, turnover and psychological suffering. Machine learning models that evaluate workload patterns, patient acuity statistics and personal sign of stress can predict the risk of burnout in nursing staff, physicians and other health workers with a potential application for targeted interventions [3,50-52]. By signaling teams and individuals approaching the limits of threshold stress, these resource systems enable prospective action to support workload resilience and to proactively stem the tide of escalating care delivery capacity failures. AI-powered telemedicine platforms have constructed sustainable delivery models that ensure continuity in times of asset abandonment, epidemics, or in response to tradition access isolation. Computer vision algorithms allow for remote physical exams, natural language processing enables automatic collection of medical histories and diagnostic AI aids in allowing the clinician at a distance to make well-informed decisions without access to specialized consultation. Among others, these have been particularly useful for remote rural residents and elderly/adult individuals with mobility impairment or when there is disaster-related infrastructure damage of community facilities.

Healthcare supply chain resilience has been transformed with AI-enabled demand forecasting, inventory optimization and logistics coordination platforms. During the pandemic, forecasting models enabled by machine learning also accurately predicted medicine needs, medical supply demands and logistics around vaccine distribution in a way that reduced stockouts and waste. AI platforms induced by block-chain were developed for transparent supply chain and proof of authenticity: to prevent counterfeit medical product and disruption of supply. These two applications showcased how AI could help make care supply networks robust to planned and unplanned disruptions. AI-based tools for infectious diseases AI applications for infection control and outbreak management have strengthened institutional capacity to respond to infectious disease threats. Computer vision tools track if healthcare workers are washing their hands, keeping a safe distance and wearing masks and gloves, giving instant feedback to help them change behaviors that can spread the infection. Contact tracing algorithms quickly reveal probable exposure groups for timely isolation and testing. AI-equipped sensors in environmental monitoring systems detect the presence of pathogens and assess outbreak risk by considering various aspects such as environmental factors, patient flows, and characteristics of specific facilities. Table 2 shows challenges, concerns, and future directions in AI-enhanced resilience.

Artificial intelligence in climate and environmental resilience

Artificial intelligence for climate change adaptation and environmental resilience is a crucial frontier where machines address existential threats to ecological and human systems [53-57]. Machine learning models that utilize satellite imagery, climate data, and ecological metrics have transformed our ability to monitor ecosystem health, forecast environmental change, and inform adaptation responses. Deep learning techniques applied to multispectral remote sensing imagery are capable of identifying small variations in vegetation health, water quality, biodiversity shifts and land use changes that could not have been observed by traditional monitoring methods, both, with higher spatial definition and temporal accuracy. AI-driven biodiversity monitoring systems that process acoustic data and camera trap images as well as environmental DNA samples to monitor species populations, spot ecosystem stress levels, and predict tipping points have revolutionized assessment of ecosystem resilience. With millions of wildlife images learned by the CNN, automated species identification and population abundance estimation becomes possible spanning large geographical area that otherwise presented an unprecedented scale and continuousness in ecological monitoring. They recognize early warning signals of ecological degradation which allows for proactive conservation measures before damage becomes irreversible.

Predictive climate risk models that apply AI together with earth system science have improved community and infrastructure resilience planning [58,59]. Algorithms for machine learning process historical climate and oceanographic records, together with atmospheric and socioeconomic data, to produce local-scale streaming forecasts of risks of flooding and droughts, extreme weather events, or sea-level rise impacts in high resolution. These are the predictions used to inform urban planning, agricultural adaptation measures, water resource management and disaster preparedness programs that promote building resilience as opposed to just responding after the fact. AI-enabled precision agriculture systems that fine tune to worldwide variability in climate help maximize the resilience of crops by empowering informed decisions on when to plant, how much water and fertilizer are required during daily irrigation cycles, pest control, harvest scheduling. Real-time crop health drone to monitor computer vision systems that observe crop health and detect disease outbreaks, insufficient nutrients and water stress before they drastically reduce yield. RMS approaches specify how resources should be distributed across the farms, so as to achieve high productivity while mitigating against weather extremes and climate uncertainty. The technologies are particularly beneficial to smallholder farmers in developing regions at risk of food security shocks.

AI applications on hydrological forecast, drought prediction and water allocation optimization have also significantly enhanced the resilience of water resource [60,61]. Machine learning algorithms that study patterns in precipitation, snowpack levels, soil moisture information and climate predictions have given water officials the potential to make better decisions about reservoir operations, predict when they face water shortfalls and take conservation action in advance. AI-based allocation algorithms are used to manage competing water requirements during drought across agriculture, urban and environmental users while maintaining long-term water security. AI-powered forest fire prediction and monitoring solutions have also improved community resilience in areas with high frequency of wildfires. Depositing satellite images, weather forecasts, vegetation moisture readings and historical fire data into deep learning models lets officials forecast ignition risks and follow fires' behavior with uncanny accuracy. Computer vision systems can catch smoke plumes early, which means a quick reaction before fires get out of control. AI-driven resource coordination strategies place firefighting resources in the right place at the right time to maximize burn suppression effectiveness and minimize negative impacts on high-value assets such as communities, infrastructure, and critical ecosystems. Ocean and marine ecosystem observation for resilience with AI spans from coral reef health, fisheries management to detection of marine pollution. Computer vision algorithms have been integrated into underwater drone systems to remotely survey reef ecosystems and document bleaching events, species diversity, and recovery patterns. Machine learning algorithms can forecast e.g. harmful algal blooms, optimize sustainable fishing quotas, and trace illegal fishing practices protecting the resilience of our oceans to climate change and other man-made stressors.

Table 2 Challenges, concerns, and future directions in ai-enhanced resilience

Sr. No.	Challenge Category	Specific Issue	Impact on Resilience	Mitigation Approach	Future Direction
1	Data Quality	Limited historical data for rare extreme events	Models poorly calibrated for unprecedented scenarios	Synthetic data generation, physics-informed learning	Hybrid models combining mechanistic understanding with data-driven learning
		Non-stationarity due to climate change	Historical patterns fail to predict future conditions	Adaptive learning, continual model updating	Online learning systems evolving with changing environment
		Geographic data gaps in vulnerable regions	AI tools ineffective where most needed	Transfer learning, satellite data democratization	Global sensor networks with open data policies
2	Algorithmic Bias	Resource allocation bias against marginalized groups	Exacerbated inequalities during crises	Fairness constraints, diverse training data	Participatory AI design with affected community involvement
		Underrepresented populations in training data	Reduced prediction accuracy for vulnerable groups	Targeted data collection, synthetic augmentation	Federated learning enabling privacy-preserving collaborative training
		Cultural appropriateness of mental health interventions	Ineffective support for diverse cultural contexts	Culturally-adapted models, multilingual systems	Community-customized AI tools reflecting local values
3	Privacy Concerns	Sensitive personal health data collection	Privacy breaches undermining trust in systems	Differential privacy, encrypted computation	Homomorphic encryption enabling computation on encrypted data
		Location tracking for epidemic control	Surveillance infrastructure outlasting crisis justification	Time-limited permissions, decentralized contact tracing	Privacy-preserving proximity detection without centralized tracking
		Mental health monitoring raising surveillance fears	Resistance to adoption limiting potential benefits	Transparent data governance, user control	Local processing minimizing data transmission
4	Interpretability	Black-box models in clinical decision support	Clinicians unable to validate recommendations	Explainable AI techniques, attention mechanisms	Inherently interpretable models with comparable performance
		Complex ensemble models obscuring reasoning	Difficulty identifying and correcting systematic errors	Model distillation, local explanations	Causal models revealing underlying mechanisms
		Policy-makers unable to understand climate model predictions	Reduced confidence in adaptation recommendations	Visualization tools, scenario narratives	Interactive exploration interfaces for complex predictions
5	Technology Access	Digital divide creating resilience inequality	Vulnerable populations excluded from AI benefits	Low-cost deployment, offline capability	Edge AI requiring minimal connectivity and computing resources
		Lack of technical expertise in developing regions	Unable to deploy or maintain sophisticated systems	Capacity building, no-code platforms	Automated machine learning democratizing AI development

		Infrastructure limitations in rural areas	AI tools unusable without connectivity and power	Distributed computing, energy-efficient algorithms	Solar-powered edge devices with local processing
6	Robustness	Adversarial attacks on image recognition	Compromised disaster assessment and medical diagnosis	Adversarial training, certified robustness	Robust architectures provably resistant to perturbations
		Model poisoning through corrupted training data	Systematic failures in critical resilience systems	Data validation, anomaly detection	Blockchain-verified training data provenance
		Brittleness to distribution shift	Performance degradation when conditions change	Domain adaptation, uncertainty quantification	Continual learning maintaining performance across contexts
7	Over-reliance	Human skill erosion from automation	Inability to function when AI systems fail	Hybrid intelligence, skill maintenance programs	Human-AI teaming preserving human capabilities
		Vulnerability to systemic AI failures	Cascading resilience breakdowns	Redundant non-AI backup systems	Graceful degradation with failover mechanisms
8	Integration	Legacy system incompatibility	New AI tools unable to interface with existing infrastructure	API development, middleware solutions	Modular architectures with standardized interfaces
		Organizational resistance to algorithmic decisions	Limited adoption despite technical capability	Change management, participatory implementation	Co-design processes building organizational ownership
		Regulatory frameworks lagging technology	Unclear legal status and liability of AI decisions	Policy engagement, regulatory sandboxes	AI-specific governance frameworks addressing unique characteristics
9	Environmental Impact	High energy consumption of model training	Carbon footprint undermining climate resilience goals	Efficient architectures, renewable energy for computing	Green AI prioritizing efficiency alongside performance
		E-waste from sensor and computing infrastructure	Environmental degradation from technology deployment	Sustainable design, circular economy principles	Biodegradable sensors and recyclable computing hardware
10	Accountability	Unclear responsibility for AI errors	Difficulty assigning liability for harmful outcomes	Transparent decision provenance, audit trails	Legal frameworks defining AI accountability
		Opaque decision chains in multi-agent systems	Tracing error sources in complex interactions	Comprehensive logging, causal attribution analysis	Explainable multi-agent coordination with clear responsibilities
11	Trust	Lack of confidence in AI recommendations	Stakeholders ignore useful predictions	Validation studies, performance transparency	Calibrated confidence estimates with error bounds
		Past AI failures undermining credibility	Resistance to adoption based on prior disappointments	Realistic capability communication, incremental deployment	Gradual trust building through demonstrated reliability
12	Ethical Concerns	Autonomous triage decisions in resource scarcity	Algorithmic life-or-death choices lacking ethical grounding	Human-in-the-loop for critical decisions, ethical constraints	Value-aligned AI embedding ethical principles in optimization

Artificial intelligence applications in infrastructure and supply chain resilience

AI-based technologies to predict failure, autonomous operation and quick recovery from disruptions have substantially improved resiliency of critical infrastructure [62-64]. Utilities AI enabled power grid platforms demonstrating unprecedented resilience with real time load balancing, fault detection and self-healing are being built. Machine learning algorithms constantly process transmitter line, transformer and distribution network information from sensors to predict when equipment will fail before outages can happen and then enable the maintenance crew to act on that data before a customer is left without service. In the occurrence of severe weather or equipment failure, AI-enabled grid management systems re-route power flows, isolate damaged areas then restore service to unaffected portions in minutes instead of hours. A highly impactful application of AI in energy resilience is the optimization of microgrids to function independently during disruptions on the main grid with the aid of distributed energy systems. Adaptive extensional learning algorithms handle battery storage, renewable integration and load prioritization to maximise energy availability in case of emergencies and ensuring the system stability. Such "smart" microgrids have become a lifesaver for hospitals, public safety facilities and disaster-prone communities where the regular power supply gets cut during disasters. AI-driven demand forecasting, inventory optimization and logistics coordination systems have transformed supply chain resilience by dynamically adjusting to disruptions. The firm analyzes years of transaction data via machine learning models to forecast customer demand based on the MPE across multiple dimensions, and hence calculates the optimal stocking levels. Throughout the pandemic, companies that had deployed AI-powered supply chain solutions also showed a much greater resilience in keeping their offering available while competitors experienced extreme product shortages.

AI has a significant potential for improving transportation network resilience via traffic management, route optimization and autonomous vehicle coordination. Real-time traffic information, weather and incident reports are processed by machine learning algorithms that dynamically adjust signal timing, propose alternative routes or coordinate rerouting of emergency vehicles to keep network flow when disruptions occur. Prediction maintenance systems for transportation infrastructure to identify declining roads, bridges and rail lines in advance of failure avoiding domino effects on travel networks. Cyber resilience is a key battle field where AI provides both defense and offense. In machine learning-based IDS, abnormal activities that may indicate systems attacks are recognized by examining traffic characteristics of network, user actions and the logs generated from system. Machine learning models developed on large collections of malware signatures and attack templates are effective to quickly identify and respond to unknown threats. Adversarial artificial intelligence, though, is an increasingly challenging approach as attackers use more complex algorithms to circumvent detection systems and compromise AI-driven infrastructure.

The network security for critical infrastructure cases has been adapting to AI-driven threat intelligence platforms that consolidate the information from a broad variety of sources, recognize attack patterns and anticipate new threads' vectors [65-67]. These solutions allow for security posture to be updated proactively before an attack materializes, moving from the traditional model of reacting to incidents towards a predictive threat prevention framework. Independent autonomous security orchestration platforms work across your systems by connecting the dots, isolating impacted parts and, in general, helping you keep services up and running. The resilience of production has been improved by artificial intelligence-based productivity optimization, quality control and supply chain synchronization. Computer vision systems look over goods with way better consistency than humans, catching defects that would slip past any human inspector. Predictive maintenance algorithms work to prevent unexpected downtime by predicting machine failures and scheduling maintenance on the schedule. AI-enabled digital twin technologies generate virtual copies of factory floors to test and optimize scenarios without physically disrupting operations.

Artificial intelligence in social and community resilience

AI systems have contributed to social resilience by enhancing community engagement and coordination for relief work and resource management in time of crisis [68-70]. Social network analysis techniques detect community structures, influential processors and information diffusion processes for efficient crisis communication and collective action. During a disaster, AI-driven systems pool data from social media, emergency calls and official sources to generate real-time situation awareness which allows for coordinated responses and the delivery of material aid in targeted locations [55,71-73]. AI has contributed to educational resilience in the areas of personalized learning, student support and institutional disruption response. Personalized learning platforms use machine learning to customize content, pacing and assessment to the needs of each student, allowing schooling to continue with flexibility amidst change. And amid COVID-19 school shutdowns, AI-augmented online learning systems showed the potential for technology to maintain educational strides when it is no longer possible to deliver them via traditional classroom instruction. Early warning systems for student learning, performance and behaviour that flag students who are at risk of trailing off allows intervention while on course.

AI-powered tools for assessing community vulnerability consolidate various data sources such as demographics, economic indicators, health statistics and infrastructure quality to determine where people and places are at higher risk from disasters [26,74-76]. These AI geospatial platforms support targeted resilience investments, focusing on the areas of highest needs and vulnerabilities. Machine learning model predictions on how different population groups will react to different disaster scenarios drive equitable allocation of resources and design of support systems. Emergency response coordination has been revolutionized by AI platforms; they maximize resource allocation, person recovery and relief dissemination in disasters. The aerial imagery and drone footage processed by computer vision systems are quickly evaluated to assess the extent of damage, locate survivors in need and understand where infrastructure is damaged. Natural language processing model for the analysis of emergency communications to enable priority assignment and coordination among multiple responding agencies. These systems achieve reduced response time and more effective resource utilization. Food security resilience utilizes AI to optimize agricultural production, supply chain management and early warning systems for crop failures or risk of food shortages [77-79]. Artificial intelligence algorithms processing climate, market and production data together with socioeconomic indicators forecast the onset of food crises months in advance and thereby allow for earlier humanitarian response beforehand. Technologies for precision agriculture maximize crop yields and also impart resistance to climate vagaries, pest plagues and resource limitations. AI-based simulation and optimization tools have also advanced the field of urban resilience planning by appraising infrastructure investment, land use policy and disaster preparedness options. Modeling cities as agent-based systems, researchers can use these to test how a city responds to specific kinds of disruptions and determine where the most vulnerable spots are before implementing interventions. As an application, we present machine learning algorithms developed to optimize city design for climate adaptation in terms of heat island reduction, flood risk decrease, green area distribution and transport network redundancy.

Artificial intelligence techniques and algorithms in resilience applications

Deep learning models serve as backbones of the most sophisticated resilience systems, and convolutional neural networks have proven to be effective in imagery tasks like medical diagnosis, disaster damage assessment, ecosystem monitoring or infrastructure inspection [80-83]. Recurrent neural networks (RNNs) and RNN variants, especially Long Short-Term Memory (LSTM) networks, offer time series prediction capability which are critical for applications such as climate forecasting, disease modeling and power grid load prediction. The Transformer architectures have transformational impact that goes beyond natural language processing (NLP) for mental health support, and clinical decision support, and crisis communication analysis. Reinforcement learning (RL) is a class of algorithms that solve the problem of sequential decision-making under uncertainty and play increasingly important roles in resource allocation, emergency response coordination, or adaptive management to complex systems. Deep Q-networks and policy gradient methods allow AI agents to learn the best strategies by playing against a simulated or actual environment, finding solutions that human experts might miss. Multi-agent reinforcement learning is a promising approach to coordinate multiple autonomous systems, which is widely needed for swarm robotics in disaster recovery, distributed energy management and collaborative infrastructure maintenance.

Ensemble learning algorithms that aggregate multiple models are often also superior in the sense of being more robust and reliable than individual models, which is important for applications at high stakes of failure where incorrect predictions result in relatively severe costs [84-86]. Random forests, gradient boosting machines, and so on), as these ensemble approaches combine predictions from multiple models in such a way that lowers the chances of overfitting while increasing generalization to new settings. These methods are particularly useful for climate models, disease outbreak forecasting and infrastructure failure prediction in which uncertainty quantification is critical. Transfer learning techniques allow AI models to be adapted for local resilience contexts even when data are scarce. Pre-trained models, which can be used for general image recognition, natural language understanding (NLU), or pattern detection tasks, can be fine-tuned to tailor to any number of domains such as diagnosing rare diseases; identifying endangered species in a region; and assessing climate risk analytics focused on particular regions. This capability democratizes deployment of AI, allowing underfunded organizations and communities to utilize advanced technologies without the need for extensive infrastructure for huge data collection and training.

GANs create artificial datasets for training robustness models when little or no real data is available, and the latter is either sensitive or prohibitively difficult to collect [18,87-89]. Synthetic data generation also solves the challenge of privacy in mental health and medical applications where training models are constructed with anonymized sets that preserve statistical properties of the data while ensuring user privacy. In such healthcare resilience applications with privacy regulation about sharing patient data, federated learning architectures facilitate the shared training of models over distributed datasets without centralizing sensitive information. Some organizations develop common models using local data, and exchange model updates only instead of raw model. In this way, we may enjoy benefits associated with going large at the training time and yet operate within a regime that respects privacy, to generate enhanced predictors which satisfy both regulatory and ethical norms.

They have the potential to work well for analyzing complex relational structures, such as social networks, supply chains and ecological food webs etc., as well infrastructure interdependencies. These architecture exploit regularities in the network topology, node attributes and edge relationship to predict cascade failures for estimating critical parts of the network and optimizing resilience. Applications range from vulnerability evaluation of power grid to modeling epidemic spread on social networks. Explainable AI techniques have become important to meeting trust and accountability needs in resilience solutions, where human stakeholders need a means of understanding the reasons behind AI decisions. Models utilizing attention mechanisms, saliency maps or local interpretable model agnostic explanations can highlight which input features contribute to a prediction and enable domain experts to validate the decision-making process of a model and discover biases in the underlying data. Interpretability is especially important for scenarios such as clinical decision support, disaster response coordination and policy making where AI suggestions drive high stake decisions.

Challenges in artificial intelligence-enhanced resilience

Quality and access to data remain two of the major challenges which hinder AI for resilience applications [3,90-91]. In many resilience settings few and rare events are observed or only small amounts of historical data are available, so that training of robust models for generalization to new situations is hardly possible. Climate change causes non-stationarity, which means that past patterns may fail to mimic those of the future, simulating models on historical data. Infrastructure for data collection is lacking in many of the most vulnerable areas, leading to geographic biases where AI approaches work well in places with ample data and do not perform as needed in those areas with the highest resilience needs [10,92-94]. Ethical Considerations Algorithmic bias and concerns for fairness present ethical issues in AI resilience applications. Suppose the past can be exploited for optimal decision-making, but the data used to train the models preserves or exacerbates existing disparities. For instance, facial recognition systems used in disaster response might work poorly for some ethnic groups, mental health chatbots may not support diverse cultural settings, and risk prediction models might underestimate vulnerability in communities that are poorly represented in the available data.

The balancing of the pertinent privacy and data security issues arises from the need to collect data for an effective AI system [95,96]. The mental health monitor needs to access personal and sensitive information, which might lead to attitude of abuse towards the users when they feel that their privacy is being violated. The use of location tracking for epidemic control or disaster response can lead to efficient coordination, but such surveillance infrastructure might live beyond the crisis rationale. Interpretability of models has been a challenge to trust and AI resilience in stakeholders. Intelligent deep learning models are black box systems such that users have no knowledge of prediction rationales, error identification is hard, and decision contestation becomes a problem. In high stakes situations such as medical diagnosis, disaster response or climate adaptation planning stakeholder need explanations for the AI results they get in order to vouch their appropriateness and keep a human oversight of key decisions. This has the potential to not only result in technology haves and have-nots, but also in resiliency haves (who can develop advanced AI capabilities) and haven'ts (those with a lack of digital infrastructure, skills or funding to deploy such systems). The deployment of AI could worsen the already existing divides in resiliency, since rural and poor areas or large parts of developing countries might not have access to connectivity, computational power, or trained human staff to deploy AI response. There could also be a resilience divide: the technologies that will enable more resilient ways of doing things might leave the most vulnerable further behind.

However, as AI-based systems start to form a vital component of the critical resilience infrastructure, their reliability and vulnerability to adversarial attacks are arguable. Adversarial examples trick image-recognition systems, possibly throwing off disaster damage assessment or medical diagnoses. Adversarial poisoning attacks could spread to the training set and impact many crucial systems. Relying on AI as a defense introduces new vulnerabilities: local failures of one's AI system, hacking or adversarial reshaping of the world can lead to systemic cascades of erosion in resilience. Human capabilities loss and overdependence Human skill atrophy, dependence can occur when the use of AI systems to automate specific classes of resiliency tasks once carried out by people. Clinicians could lose their diagnostic abilities, atrophying under the strain of too much AI decision support; emergency responders might flail when technology they had come to rely on suddenly let them down; communities might splinter without any way to organize disaster relief through AI platforms.

When integrating AI systems into an existing setting, we must address their integration as a technical and socio-technical infrastructure, again: How will they fit into this system? Legacy systems made to run SQL based commands may not be compatible with the AI platforms that are currently available; corporate cultures may resist decisions made by algorithms, and the legal system isn't always equipped to comprehend artificial intelligence's quirks of its own. The progress of AI relies not only on realization at technical-level, but also organizational deployment, training schedule, policy updating and culture-changing [97-99]. Energy consumption and carbon footprint are now bring problems: training large AI models involves huge amounts of computation, and a burden that can carry a heavy carbon footprint. The footprint of the AI runs against the goal of creating climate-resilient systems, and warrants an urgent debate of whether data-greedy compute-hungry methods are acceptable. Tiny is the New Big These can be mitigated somewhat by edge computing, model compression and efficient architectures but we must do more on levering AI to create a net positive for global environmental resilience.

Opportunities and future directions

The promise, then, for a next generation of forces is hybrid intelligence systems able to effectively exploit the malleability and limitations in human reasoning power, by harnessing the complementarity and acting as an enabler of their weaknesses. Those sorts of systems could help doctors diagnose more precisely, emergency coordinators make better decisions and conservationists aim more effective strategies for preserving ecosystems [8,100,101]. Further, the EdgeAI paradigm and distributed intelligence architectures allow us to bring in resilient mechanisms for resource-limited systems with a minimal degree of adaptation becoming necessary when it comes to cloud connection [102-104]. Edge-based computation on mobile devices or IoT sensors also enables data to be locally processed with continuous and real-time resiliency in disaster situation of no-network. The federated learning methods shine in the harmonization for models between any distributed deployments, and out of those fully eliminate the demand on aggregated sensitive data but address issues related to privacy beyond technological capacity bottlenecks.

Multimodal AI systems, for example those that incorporate data from various modalities such as image, text, sound, and sensedata, which are also light-weight offer opportunities to better monitor and predict overall resilience levels [105-106]. By pairing satellite imagery with data from social media sentiment and climate measurements with economic indices and physiological readings with computational behavior analysis we can capture the complete systems perspective that is appropriate for complex wickedness efforts resilience confronts. These next generation systems would ideally exploit the different forms of information, much in the way humans can have a hunch that incorporates knowledge from these modalities. Systems of perpetual and adaptive learning on systems that can adjust to changing environment are pivotal to deal with non-stationary environments. Rather than constantly relearn from scratch each time the environment shifts, they update in real time as new information rolls in, keeping up with data and staying mutable as climate patterns shift, diseases take on new configurations or social dynamics rearrange themselves. Possible applications for such systems include mental health interventions adapted to new stressors, infrastructure whose operations are coupled to changing patterns of use or models of conservation that adapt to changes in their environment.

The integration of causal inference with predictive AI provides an opportunity for learning the underlying mechanisms of resilience rather than correlating patterns [107,108]. Causal models would reveal true relationships that influence resilience and distinguish these from meaningless associations, making interventions more efficient. The knowledge of the causal pathways from social support to psychological resilience, from biodiversity to ecosystem stability, or from infrastructure redundancy to service continuity helps directing interventions in the variables with greatest effect. Quantum machine learning is a longer-term frontier that could transform the ability to compute for complex resilience problems. Quantum algorithms will make optimization feasible for systems that are unimaginably large for classical computers; simulate climate and ecological changes on heretofore unpublished scales; create cryptographic security guarantees, ensuring cyber vulnerability won’t damage critical infrastructure resilience. Practical quantum advantage is years off, but by developing algorithms and frameworks now, applications can be well placed to exploit the new capabilities provided by quantum as they become available.

AI democratization to no code development platforms, auto ML and accessible deployment frameworks could help communities easily build affordable resilient solutions tailored for local needs [3,8,109]. There would be less reliance on “outside experts” to create and deploy systems because communities could customize the AI tools for their needs, culturally appropriate, locally relevant and owned by that community. Resilience AI platforms in open-source support sharing of knowledge and joint development among global communities with similar problems. Ethical AI frameworks, tailored to resilience contexts, will become increasingly critical as these systems are brought to bear in life-critical decisions. Norms regarding fairness in distributing resources in times of crisis, the tradeoff between privacy and collective needs, the amount of transparency for high-stakes predictions that may result, and mechanisms for holding algorithms accountable when they fail need to accompany technical capabilities. Participatory design methods that include affected publics in the development of AI systems can help ensure technologies are tailored to the needs of a range of stakeholders/communities, promoting autonomy and dignity. Standardization and Interoperability Standardization and interoperability initiatives will facilitate how resilience AI systems work together, across organizations and geographies. Widespread data formats, common ontologies and open interfaces enable emergency response platforms to interoperate easily, healthcare systems to share capacity in the time of surge events, climate adaptation tools to be integrated across jurisdictions. International collaboration on resilience AI guidelines may contribute to a global upgrading of capacity and common knowledge development.

Impact of artificial intelligence on sustainability and long-term resilience

Use of AI in resilience frameworks has significant sustainability and long-term adaptive implications. AI-driven resources allocation minimizes waste and environmental damage, while increasing efficiency, will play an important role in supporting both the ecological sustainability and operational resilience [3,8,88]. Precision agriculture optimizes the amount of fertilizer and water, minimizing usage, all while maximizing yield; supply chain optimization decreases transportation emissions; and smart grid management is enabled to integrate renewable energy sources effectively. Savings of this kind show the associated value of sustainability and resilience. But new AI applications also have a sustainability tension built into their computer and data requirements. Models like this one, as well as the computer vision systems and other high-energy AI require so much energy to train and operate that they could be working against climate resilience. The tech industry should be burning the midnight oil on energy-efficient architectures, computing systems and data centers powered by renewables, but we also need to have a bit of earnestness about how heavy a cognitive load we're willing to pay for that benefit. Green AI, instead of just adding more computation without considering the environmental cost to a problem, tunes the amount of performance relative to energy.

It also means growing human capacities alongside technical systems, so that we form not too much dependence on AI-answers who would have their own points of failers. But resiliency skills and educations to use when technology fails or is not available are something communities can never forget. Training and education need to make it clear that these systems are AI-as-teammate, not AI-as-replacement; people must have a good sense of what they know and can do, but also what they don't understand so that they're still able to solve problems on their own. But for sustainability to be durable, technology needs to reinforce not replace human adaptability. Equity Driving considerations for sustaining resilience: exclusion from AI may exacerbate existing vulnerabilities. Technology-based resilience strategies could undermine groups lacking connectivity, technology skills or economies of scale to make use of ad options. With sustainable policy and cheap platform access, low resource required and capacity building programs were feasible. International co-operation and knowledge transfer could help developing countries to jump forward to more advanced resilience systems without having to go through the technological development stages seen in developed countries.

4. Conclusions

Preliminary findings of systematic literature review indicate AI as both a boost and pitfall for psychological, health-care, enviro-infrastructural as well as social resilience. We synthesize 176 studies across different disciplines, populations and contexts to demonstrate that the effects of AI on resilience are not limited to the simple automation or efficiency multiplier but fundamentally transform how people, organizations, ecosystems and societies anticipate, absorb adapt and recover from shock. The results prove that AI possesses much better ability to predict and is thus indispensable for the construction of proactive resilience. Machine learning can predict who is at risk for, distress, depression, anxiety and burnout in a clinically meaningful way long before these become crises with the possibility of effective intervention to decrease crisis cascade. These predictive powers apply to predicting pandemics' courses, climate effects, supply chain risks and infrastructure failures well in advance of when measures could be taken. This method permits the analysis of large, heterogenous data sets and identifies patterns and connections that are hidden in the traditional methods of analysis, which help identify protective factors, risk factors and provide a basis for targeted interventions to build resilience within multiple at-risk populations such as, children, youth, adults, healthcare workers, and seniors.

We posit AI-enabled personalization as a key contribution acknowledging that resilience is not universal but context-dependent and varies among individuals. Predictive models discovered tailor-made mental health interventions which integrate personal characteristic, history of trauma, social support network and responses to treatment that increase the response rates and thus better engagement and outcome than uniform approaches. Adaptive learning systems personalize instruction so that students are given lessons at the level that suits them and which is challenging enough to stimulate cognitive resilience. Extending to personalized risk-stratification, and treatment optimization 'personalized care' that takes into consideration individual variations, e.g. comorbidity, genomics and social determinant of health. This capacity for personalization tackles a fundamental issue in how research findings from the population level have come to be translated into individual-level therapeutic interventions, and could democratize access to advanced assessment and support previously available primarily through specialist expertise.

Optimization potentials do significantly promise anything reliable in complex ecosystems. Humans observe that through rational AI we attend shortages in resource allocation within healthcare systems during pandemics, demand variability in energy microgrids and supply chain distortion. AI can identify disruptions and threats faster and with more precision than the human eye. Predictive maintenance is the way when dealing infrastructure where it's not prone to failure and one can save resources on maintenance. These applications raise the efficiency of daily life, and work as something on which to codify the flexibility we need in crisis time, re-writing its separateness from performance, articulating how a fast response can be made to work with speed and not against it. The review does also highlight, however, some very real obstacles that chill our effervescence and obstinately need to be avowed. Algorithmic bias has a higher probability of perpetuating and/or even exacerbating inequities when the training data reflect prior patterns of discrimination, or is it systemically biased toward under-representing disadvantaged populations groups. The digital divide which results in unequal access to AI-powered tools and interventions will inevitably lead to a bifurcation of resilience landscape where the privileged people become more advantaged and neglected people left behind. Privacy and security issues arise as the main challenge because sensitive personal data is needed of some AI resilience applications. Prediction of mental health relies on the monitoring of communication and behavioral patterns as well as social relationships, which raises understandable concerns about surveillance and misuse. Healthcare apps have access to the protected health information and require strong lever of protection against unauthorized access can harm patient's health and autonomy.

The reliance problem, and the generalizability problem, are limiting AI application for emergent contexts or extremities where resilience is most crucial. Machine learning systems trained on historical data can experience catastrophic failures when presented with novel events not previously encountered during their training, as some predictions did during the early days of COVID-19 pandemic. Finally, the black box nature of many advanced algorithms makes it hard to trust decisions that are of good quality and does not help lessen doubt when individuals or critical matters are at stake. Technological wizardry collapses in just the crises it has been designed to cope with solutions, choice of AI approaches will erode human judgment and adaptive expertise. Ethical issues will continue to surface as AI-enabled resiliency applications are developed; there needs be conversation among stakeholders concerning appropriate use and implementation mechanisms, as well as accountability methods for the wicked intentions of politicians. No less important, it identifies strategic opportunities for the development of AI-Enhanced Resilience along several dimensions. AI systems that are explainable, and produce transparent rationales as to how they make their predictions or recommendations can bear some scrutiny while allowing an appropriate level for human oversight. Instead, with human-centered design, AI tools might more effectively account for what users actually need and can't do themselves. Federated learning for privacy-preserving approach continues to be developed, which has the potential to harness intelligence from distributed data and still respect individual privacy. Producing more inclusive datasets as well as building fairness-aware algorithms should result in less biased categorization and a more equitable spreading of benefits across all sectors of society You have governance structures which are about mixing innovation and protection to deal with ethical issues while also encouraging responsible development and deployment. Given the multidisciplinary nature and cross-linked character of both AI and resilience, interdisciplinary cooperation seems an imperative.

Psychologists, data scientists, suppliers, programmers, ethicists, siderographers and community partners are necessary to build a technology that enhances the conditions necessary for a truly resilient life. The way ahead is to forego disciplinary silos in favor of an integrative perspective on human technological adaptation, for which more cross-breeding between models of psychological resilience as well as those from machine learning or socio-technical systems. The future needs more investigation into several points to be followed up. In particular, prospective AI interventions as causal agents helpful to resilience trajectories throughout people's whole lives will help untangle the current incomplete patterns of causality apparent in cross-sectional research design. This could be verified via random controlled trials comparing AI-augmented integrity versus normal integrities when being tried on different populations and in diverse settings to ascertain its effectiveness as well as limits. A composite analysis of how AI is intertwined with different aspects of resilience can also shed light on potential unanticipated side-effects and trade-offs which must be taken into account from the perspective of an entire system. International comparisons across cultures, across socioeconomic classes and across different parts of a given culture will be important to consider equity implications and guide the strategy for inclusion deployment. Emerging capabilities in AI such as large language models, multimodal learning, and embodied AI have not been widely recognized so far for resilience applications. With the mounting threats posed by pandemics, climate change, natural disasters and mental health crises among other disruptions arising for societies to withstand, AI is a potent force that should guide us in our journey toward resilience that is inclusive, sustainable and essentially human.

Conflict of interest

The authors declare no conflicts of interest.

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