NAVIGATING AI IMPLEMENTATION: A THREE-DIMENSIONAL FRAMEWORK FOR PEOPLE WITH DISABILITIES IN MALAYSIAN COMMUNITY-BASED REHABILITATION

OMAR, Z. F.[1*] – MIOR HARUN, M. H.[1] – MOHD ISHAR, N. I.[1] – MUSTAPHA, N. A.[1] – ISMAIL, Z.[1]

[1] *Arshad Ayub Graduate Business School, Universiti Teknologi MARA (UITM), Selangor, Malaysia.*

**Corresponding author*
e-mail: zoelfazlee[at]uitm.edu.my

(Received 29th October 2025; revised 29th December 2025; accepted 15th January 2026)

Abstract. Artificial Intelligence offers significant potential to enhance disability support, yet its adoption in Malaysia's Community-based Rehabilitation system remains inconsistent due to diverse user needs, limited infrastructure, and uneven practitioner readiness. In Malaysia, Community-based Rehabilitation practitioners lack systematic tools for Artificial Intelligence adoption, leading to wasted resources and technology abandonment. This study conducted a systematic literature review of 27 studies published between 2020 and 2025, following PRISMA guidelines, to examine Artificial Intelligence-enabled interventions for persons with disabilities and identify determinants of successful community implementation. Evidence shows that effective Artificial Intelligence deployment depends on three interdependent domains which are specific functional needs, participation-focused life goals, and contextual enablers such as connectivity, device access, workforce capacity, governance, and affordability. These domains consistently shape feasibility, safety, and real-world impact across healthcare, education, and rehabilitation settings. Based on these findings, the paper introduces a Three-Dimensional Framework that positions a person with disabilities' assessment within a functional-life-context diagnostic space to guide Artificial Intelligence prescription in Community-based Rehabilitation centres. The model provides a practical, evidence-based tool for matching technology to individual needs while accounting for environmental realities, thereby improving decision-making, reducing technology abandonment, and supporting equitable Artificial Intelligence adoption in Malaysian community rehabilitation.

Keywords: *artificial intelligence, community-based rehabilitation, persons with disabilities, conceptual framework, diagnostic tool*

Introduction

The Fourth Industrial Revolution (IR 4.0) has introduced Artificial Intelligence (AI) as a powerful force for societal transformation. For people with disabilities (PWDs), AI promises a new era of inclusion, offering solutions that range from AI-powered screen readers and speech synthesis to intelligent prosthetic limbs and assistive robots (UNICEF, 2022). However, this technological potential is often unrealized. A significant "implementation gap" exists between the creation of advanced AI and its practical, successful adoption by the people who need it most. Currently, the Malaysian government has shown a strong commitment to the welfare of PWDs through policies such as the Dasar Orang Kurang Upaya (National Disability Policy) and the Persons with Disabilities Act 2008. The backbone of disability services at the community level is the Community-based Rehabilitation (CBR) program, known locally as Pusat Pemulihan Dalam Komuniti (PDK). These centers are the primary touchpoint for over 781,131 PWDs nationwide, providing therapy, education, and vocational training (JKM, 2023). As AI technology becomes more accessible, CBR practitioners and PDK staffs

eISSN: 2716-6481
https://doi.org/10.55197/qjssh.v7i1.947

are on the front lines of its implementation. They face a critical challenge as how to navigate the complex landscape of AI solutions. A practitioner may be aware of a high-cost, high-tech AI tool but unsure if it suits a client in a rural setting with limited internet access. Conversely, a simple, free AI-powered app on a smartphone might be overlooked, despite being a perfect fit. This "one-size-fits-all" or ad-hoc approach to AI prescription leads to wasted resources, technology abandonment, and frustrated users (Wang et al., 2025; Bzikowska-Jura et al., 2021; Sangers et al., 2021; Rowland et al., 2020). Moreover, the growing national AI agenda and education or ICT policies in Malaysia create an enabling policy backdrop for deploying AI-infused assistive technologies (AT) for persons with disabilities. However, empirical studies indicate that implementation remains nascent and uneven across sectors and geographies (Zainal and Zainuddin, 2020).

Research on Malaysia-specific use cases shows that AI and AT are being trialed in education and vocational training, suggesting that such tools can improve access to information, learning, and vocational outcomes when aligned with user needs (Amdan et al., 2024; Istiyati et al., 2023; Chin and Piragasam, 2021). The literature highlights AI's potential in health-related diagnostics, monitoring, and rehabilitation which are capabilities that can be adapted to disability services, but emphasizes that safe, equitable adoption requires governance, workforce training, and context-sensitive implementation (Denecke and Baudoin, 2022; Matheny et al., 2020). Despite these opportunities, interlocking barriers constrain population-level benefits such as gaps in access to and affordability of AT echo global shortfalls infrastructural and rural-urban digital divides limit AI uptake, limited AT literacy among users, educators, and employers, and policy-to-practice implementation gaps hinder procurement and standardization of accessible AI tools (Soares and Benetti, 2025; Shukla, 2022). Empirical investigations of user experience further underscore that the assistive value of these technologies depends on inclusive design, user training, and organizational willingness to adopt AT where factors frequently reported as lacking in Malaysian studies relating to visually impaired users and their employment accommodations (Manirajee et al., 2024; Rehman et al., 2021). Accordingly, the evidence synthesis points to a dual imperative for Malaysia are to leverage national AI initiatives and education policy to scale effective AI-enabled AT, and simultaneously to address affordability, infrastructure, co-design with persons with disabilities, workforce capacity, and procurement mechanisms to ensure that AI translates into equitable, usable, and sustainable assistance for people with disabilities (Shukla, 2022; Zainal and Zainuddin, 2020). Therefore, this paper aims to develop a novel conceptual framework to serve as a diagnostic tool for Malaysian CBR practitioners. This framework is not based on arbitrary factors but is systematically developed from a comprehensive review of existing academic literature, providing an evidence-based tool for person-centered AI implementation.

Literature review

Malaysia’s strategic AI agenda (AI-RMAP) and complementary education and ICT policies provide a policy framework that could enable the deployment of AI-infused assistive technologies (AT) for persons with disabilities. However, empirical evidence indicates that implementation remains largely pilot-scale and uneven across sectors and geographies (Zaidi, 2025). AI-augmented AT which ranging from intelligent speech and vision tools, adaptive learning systems, and robotic aids to AIoT devices and personalized software has demonstrated potential to improve healthcare, rehabilitation,

eISSN: 2716-6481
https://doi.org/10.55197/qjssh.v7i1.947

education, employment, and everyday independence for people with diverse impairments (Eziamaka et al., 2024; Pancholi et al., 2024; De Freitas et al., 2022; Zdravkova et al., 2022). Malaysia-specific research documents emerging applications and sectoral experimentation but also highlights persistent on-the-ground constraints in uptake among visually impaired learners, employees with disabilities, and vocational trainees (Arifin et al., 2025; Kim et al., 2024). These opportunities are counterbalanced by structural barriers such as large unmet AT needs and affordability gaps, rural-urban infrastructure and connectivity deficits, fragmented terminology and procurement practices, and limited digital or accessibility literacy among users and intermediaries that constrain scaling of AI-based solutions in Malaysia (Kamrozzaman et al., 2025; Lourenço et al., 2025; Shukla, 2022). Moreover, global and disciplinary analyses caution that AI systems can perpetuate exclusion or bias unless designed with fairness, participatory co-design, and disability-inclusive governance, underscoring the need for contextualized, ethical adoption frameworks and workforce capacity-building in Malaysian deployments (Umucu, 2025; Smith and Smith, 2021; Guo et al., 2020). Consequently, any AI solution intended for a specific Malaysian person with a disability must be person-centered, low-cost or sustainably financed, co-designed with the user and local stakeholders, interoperable with existing services, and sensitive to infrastructure and literacy realities to translate AI's technical promise into equitable, usable, and scalable assistance (Soares and Benetti, 2025; Eziamaka et al., 2024; Latif et al., 2023).

AI intervention for a person with disability

Artificial intelligence (AI) interventions for persons with disabilities in Malaysia are at an emergent but uneven stage where national strategy documents and digital-education policies establish an enabling intent. However, implementation remains largely pilot-scale and concentrated in pockets of healthcare, rehabilitation, education, and community-based services rather than at a population scale (Shukla, 2022; Hasan et al., 2021). In health and rehabilitation, robotic systems, sensorized wearables, machine-learning prognostic models, and AIoT platforms have demonstrated the capacity to personalize therapy, supply real-time biofeedback, and extend clinic interventions into home and community settings (Banyai and Brișan, 2024; Iberahim et al., 2024; Jeter et al., 2024; Bonanno et al., 2023; Guo et al., 2023; Campagnini et al., 2022). Furthermore, major barriers restricting effective AI intervention in Malaysia mirror global assistive-technology gaps which combine with local workforce and governance deficits to limit the safe, equitable scaling of AI systems for disability support (Koshy et al., 2025; Shukla, 2022). Crucially, AI systems risk introducing or perpetuating bias and inequity unless development and deployment follow disability-inclusive design, fairness testing, and transparent governance and unless outcomes are monitored with standardized AT definitions and metrics (Umucu, 2025; Smith and Smith, 2021; Guo et al., 2020). Therefore, effective AI interventions for a specific person with a disability in Malaysia are most likely to succeed when they (a) address a clearly defined functional need, (b) combine validated AI modalities with low-cost, interoperable hardware and community delivery models, (c) embed co-design with the user and local clinicians or therapists, and (d) are supported by capacity building, procurement pathways, and governance aligned to national AI and AT policy aims (Arifin et al., 2025; Zaidi, 2025; Epalte et al., 2023; De Freitas et al., 2022; Matheny et al., 2020).

Community-based rehabilitation AI mapping tool for person with disability

Community-based rehabilitation (CBR) staff in Malaysia require a practical diagnostic-and-mapping tool that translates a person with disability's (PWD's) functional profile into an appropriate AI or assistive-technology (AI/AT) category for several reasons. Firstly, PWD needs are heterogeneous and time-sensitive, so standardized, function-focused assessments enable accurate, timely matching to interventions that can alter recovery trajectories and participation outcomes (Hakiki et al., 2022). Secondly, AI-augmented AT spans diverse modalities whose technical affordances and resource implications differ markedly, so explicit mapping prevents inappropriate or infeasible deployments and helps select solutions that are interoperable with local infrastructure and caregiver capacity (Bulan et al., 2025). Thirdly, Malaysia faces structural access, affordability, and geographic disparities that constrain on-the-ground feasibility, therefore a tool that embeds context helps CBR staff prioritize low-cost or locally deliverable options and link clients to procurement and subsidy mechanisms (Newman-Griffis et al., 2023). Fourthly, workforce and sectoral capacity for AI and AT remain limited, so a decision aid reduces reliance on scarce specialists by guiding referrals, standardizing triage, and indicating required training or multi-disciplinary inputs (Yunus et al., 2022). Fifthly, reliable matching supports ethical, equitable adoption by surfacing fit-for-purpose choices, reducing the risk of harm or exclusion from biased AI systems, and ensuring PWD involvement in selection and adaptation processes (Umucu, 2025). And finally, programmatic scale, monitoring, and policy integration demand common terminologies, metrics, and data to evaluate outcomes and inform procurement and national AI/AT plans, functions that a diagnostic-to-AI-category mapper can standardize across CBR centres and feed policy and research loops for continuous improvement (Kamrozzaman et al., 2025). In combination, these points indicate that a reliable, user-centred tool for CBR staff to diagnose needs and map them to AI/AT categories is not merely helpful but operationally essential in Malaysia (Hasan et al., 2021). Hence, this paper proposes the "Three-Dimensional Framework," a three-axis diagnostic tool to helps a practitioner analyze a PWD's context and identify the most appropriate type of AI intervention.

Materials and Methods

This paper was derived through a rigorous systematic literature review (SLR) conducted in alignment with PRISMA conventions and best-practice review methods. This paper performed a predefined, reproducible search strategy across multiple bibliographic databases using keyword sets combining terms for “artificial intelligence,” “assistive technology,” “disability,” and context-specific qualifiers such as “Malaysia,” and “community-based rehabilitation”, and recorded search dates and yields to enable a PRISMA flowchart of identification, screening, eligibility, and inclusion steps (Bulan et al., 2025; Lourenço et al., 2025). Titles or abstracts and full texts were screened against explicit inclusion and exclusion criteria with dual independent reviewers and a prespecified protocol to reduce selection bias and ensure reproducibility, consistent with established SLR practice (Bulan et al., 2025; Lourenço et al., 2025). For each included study, standardized data fields, applied formal quality appraisal and risk-of-bias assessments appropriate to study design, and conducted an environmental scan to capture grey literature and implementation reports that contextualize Malaysia’s service and policy landscape were extracted (Lourenço et al., 2025). Data synthesis followed a thematic, iterative coding process with extracted evidence was coded into domains, codes were grouped into higher-order themes through constant comparison, and cross-tabulation matrices were constructed to map functional needs against AI modality categories (Lourenço et al., 2025).

Articles were included if they were, peer-reviewed journal articles or conference papers, published between 2020 and 2025 to capture the modern AI landscape, written in English and discussed the use, adoption, or implementation of AI technology for PWDs in a community or non-clinical setting. Articles were excluded if they were purely medical or surgical in focus, did not involve AI, or were reviews or meta-analyses. The initial search yielded 930 articles where 698 articles left after removing duplicates. Then 349 articles were screened by title and abstract, leaving 87 for full-text review. Finally, 32 articles met all inclusion criteria. These articles were analyzed using thematic synthesis to identify and code the core factors that determine the successful matching of an AI solution to a PWD. From these coded themes, a provisional conceptual framework was we developed. This mapping approach aligns with prior work that emphasizes the importance of thoughtful cross-links between AI classes and disability constituencies to surface risks and suitability (Guo et al., 2020). Finally, to ensure the framework's utility for policy and procurement, this paper harmonized terminology and outcome constructs against established assistive-technology taxonomies and systematic reviews so the framework can standardize assessment, guide referrals, and produce comparable monitoring indicators for national AI and AT planning (Lourenço et al., 2025) (*Figure 1*).

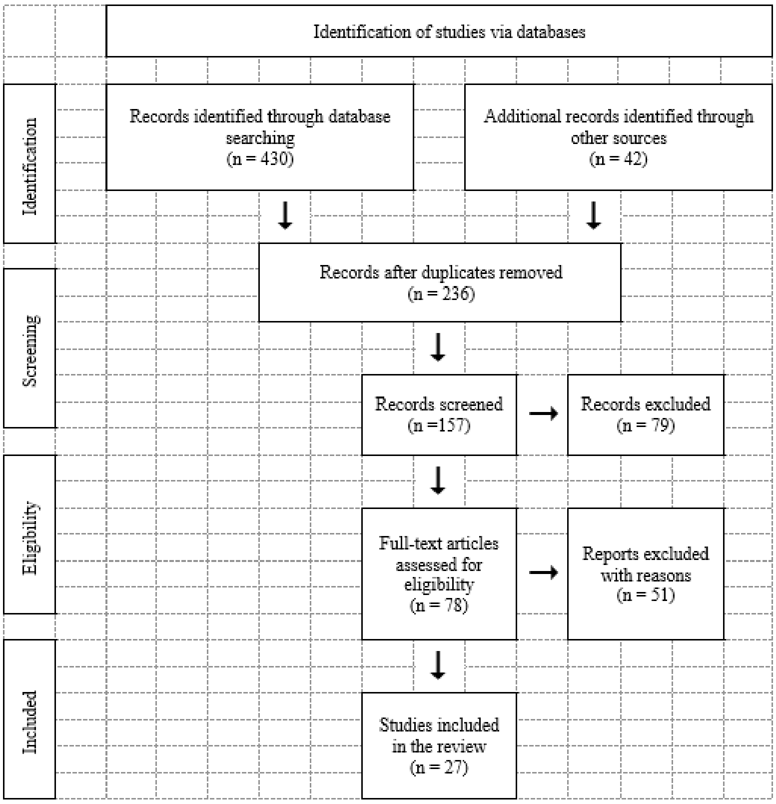

Figure 1. *PRISMA selection process of relevant literature.*

eISSN: 2716-6481
https://doi.org/10.55197/qjssh.v7i1.947

Results and Discussion

Evidence from systematic reviews indicates that AI-enabled interventions have achieved demonstrable, domain-specific successes when integrated into CBR models provided interventions are user-centered, integrated with local service delivery, and supported by training and governance structures. Systematic evidence shows that community-delivered and home-based rehabilitation programs can improve physical function and quality of life after stroke when programs are tailored to local needs in which AI enhances these effects by enabling adaptive, intensive, and feedback-rich interventions (Liscano et al., 2025; Noukpo et al., 2022). For language deficits such as aphasia, systematic reviews of AI-assisted digital therapies report promising evidence that AI can increase the intensity and individualization of practice and thereby improve language outcomes when incorporated into therapy pathways (Liscano et al., 2025). Cognitive training and social-engagement robots show potential to deliver scalable, motivating interventions for age-related or neurodevelopmental cognitive needs when embedded in community programs that provide human facilitation and monitoring (Vogan et al., 2020).

Delivery-model successes in CBR arise when AI tools are configured for community constraints such as telehealth and digital assistants extend specialist reach into homes and community centers, improving access and continuity of care while sustaining user engagement, and trials and implementation protocols for family-centered telehealth and digital assistants document feasibility, clinician acceptance, and improved service reach where outcomes that are particularly relevant for geographically dispersed CBR populations (Hurtubise et al., 2022; Valentine et al., 2021). In Malaysia specifically, community-level innovations such as game-based rehabilitation programs and community-centered deployment of digital tools illustrate how locally appropriate AI-adjacent technologies can be operationalized within CBR structures to maintain therapy intensity and participation, with positive acceptability among users and staff when supports are provided (Adenan et al., 2023). Rapid reviews of AI-enabled digital rehabilitation further report that AI features improve end-user adherence to home programs thereby translating technological capability into measurable service outcomes when combined with human oversight (Mohammad Namdar et al., 2025).

Concurrently, evidence cautions about risks and boundary conditions. AI solutions produce the best outcomes when matched to clearly defined functional needs and when safety, fairness, and usability checks are embedded into deployment in which absent co-design and oversight, AI can underperform or exacerbate inequities, underscoring the need for governance, evaluation, and clinician oversight in CBR contexts (Smith and Smith, 2021; Wiljer et al., 2021; Guo et al., 2020). Therefore, the analysis of the articles led to the consolidation of three dominant themes that to be addressed for any AI intervention to be successful. Based on the SLR, the critical factors for matching a PWD with the right AI are not just their disability, but also their personal goals and their environment. Person-centered AI prescription is achieved by identifying the Functional Domain (The Need), Life Domain (The Goal) and Contextual Enablers Domain (The Reality). These three themes form the evidence base for our proposed framework, as they represent the three essential questions a practitioner must answer before prescribing an AI solution.

Functional domain (The Need)

Successful matching of AI to function begins with granular functional assessment rather than broad diagnostic labels. Systematic reviews show that AI modalities map differentially to functional targets and that outcomes improve when algorithms are selected to match the specific sensorimotor or communicative process being trained or substituted (Boltaboyeva et al., 2025; Alouthah et al., 2024; Kaelin et al., 2021; Vélez-Guerrero et al., 2021). Thus, CBR staff must translate impairments into operational tasks so that AI designers can specify sensors, learning objectives, and performance metrics that align with principles of neural plasticity, task specificity, and rehabilitation dosing (Apostolidis et al., 2023; Mennella et al., 2023).

Life domain (The Goal)

AI interventions must be optimized for the person's participation goals rather than only for laboratory performance metrics. Evidence synthesizing CBR and rehabilitation literatures indicates that programs targeting community-relevant outcomes with embedded personalization and motivational scaffolding yield greater adherence and real-world benefit than one-size-fits-all tools (Mohammad Namdar et al., 2025; Mennella et al., 2023; Vogan et al., 2020). Operationalizing the Life Domain requires co-design with the person and caregivers to define acceptable trade-offs, to set measurable participation outcomes, and to determine tolerable error modes for AI in everyday contexts (Mohammad Namdar et al., 2025; Mennella et al., 2023; Vogan et al., 2020).

Contextual enablers domain (The Reality)

Feasibility and safety depend on local implementation conditions. Implementation science and empirical studies of AI adoption identify recurrent determinants that predict success including technology fit with existing workflows, clear implementation processes and training, regulatory and data-governance structures, resource availability, and stakeholder buy-in (Arends et al., 2025; Chomutare et al., 2022; Damschroder et al., 2022; Fujimori et al., 2022). Moreover, sociotechnical analyses warn that digital health interventions can produce unintended harms unless "dark logic" and power dynamics are anticipated such as CBR deployments must therefore assess equity risks, data privacy or security, and potential for bias or exclusion in AI models trained on non-representative populations (Ziebland et al., 2021).

A practical diagnostic tool for community-based rehabilitation (CBR) must translate heterogeneous clinical, social, and environmental information about a person with a disability (PWD) into actionable technology choices as the systematic literature review (SLR) evidence show that success depends on aligning (a) the person's precise functional requirements with (b) their life or participation goals and (c) local implementation realities. These three complementary domains jointly determine the feasibility, safety, and likely impact of AI or assistive technology interventions (Xue et al., 2025; Mennella et al., 2023; Kaelin et al., 2021). This triadic requirement is supported by rehabilitation, assistive technology (AT), and implementation science literatures, including analyses showing that success is achieved when these factors are considered together (Mohammad Namdar et al., 2025; Zaidi, 2025; Shmonin et al., 2023).

Therefore, person-centered AI prescription is achieved by identifying the position along all three axes. The model places a PWD's assessment as a point in a three-

eISSN: 2716-6481
https://doi.org/10.55197/qjssh.v7i1.947

dimensional Cartesian diagnostic space with orthogonal axes defined in *Table 1*. This orthogonal framing synthesizes rehabilitation task-matching literature, which maps AI modalities to specific functional targets, with participation and implementation literature that demonstrate that outcomes emerge only when goals and context are integrated into design and deployment (Xue et al., 2025; Bonanno et al., 2023; Vélez-Guerrero et al., 2021). It is a conceptual model that functions as a three-axis diagnostic tool for CBR practitioners. This tool guides the practitioner to analyze a PWD's situation not as a single data point, but as a position in a 3D "diagnostic space."

***Table 1**. The three-axis diagnostic model (X, Y, Z).*

No.	Axis	Domain	Details	Source
1	Axis X	Functional Domain	A clinically valid, task-level measure of the person's impairment and specific daily tasks or functions requiring remediation or substitution (e.g., reach/grasp, gait stability, speech production, information access)	Xue (2025) Alouthah et al. (2024) Kaelin et al. (2021)
2	Axis Y	(The Need)	The person’s prioritized participation goals expressed in life domains (education, employment, independent living, community participation), operationalized as measurable outcomes (e.g., return-to-work hours, independent activities of daily living, school participation rate)	Mohammad Namdar et al. (2025) Xue (2025) Noukpo et al. (2022)
3	Axis Z	Life Domain	A composite index capturing implementation feasibility: connectivity and device availability, CBR staff capacity, financing or procurement options, regulatory or privacy constraints, and equity risks (cost, literacy, bias)	Kamrozzaman et al. (2025) Xue (2025) Fujimori et al. (2022)

Operationalizing each axis

The Functional Domain axis is quantified using a 0–5 scale designed to capture the specific necessity and complexity of a required technological intervention. The anchors define the extremes of this scale: a score of 0 indicates no residual functional need for technological remediation, while a score of 5 signifies a high-priority, high-specificity task that would significantly benefit from advanced AI or Assistive Technology (AT). An example of a high-anchor score would be an individual with severe motor impairment requiring continuous support. The Life Domain axis evaluates the individual's aspirational participation goals, also rated on a 0–5 scale. The anchors for this domain differentiate between maintenance and active, high-priority change. An anchor score of 0 is assigned when no aspirational change in participation is desired by the user, indicating a goal of maintenance. Conversely, a score of 5 indicates a high-priority, high-impact participation goal, such as an immediate return to paid employment or re-engagement in formal education.

The Contextual Enablers Domain provides a critical, pragmatic assessment of the user's environment and its readiness to support a digital intervention, scored from 0–5. The anchors represent the extremes of implementation feasibility. A score of 0 depicts an environment that is entirely inhospitable to digital interventions, characterized by factors like no connectivity, no suitable devices, absent caregiver support, or no viable procurement pathway. In contrast, a score of 5 describes a fully enabling ecosystem that includes stable connectivity, appropriate device access, available funding or subsidies, trained local staff, and established data governance protocols. Therefore, this paper proposed the "Three-Dimensional Framework," a conceptual tool for the Malaysian Community-based Rehabilitation program. Developed from a systematic literature review, this framework provides a practical, three-axis model to help practitioners diagnose the needs, goals, and contexts of PWDs and map them to appropriate AI solutions. A proposed conceptual framework is shown in *Figure 2* consist of the Functional Domain (The Need), Life Domain (The Goal), and Contextual Enablers Domain (The Reality).

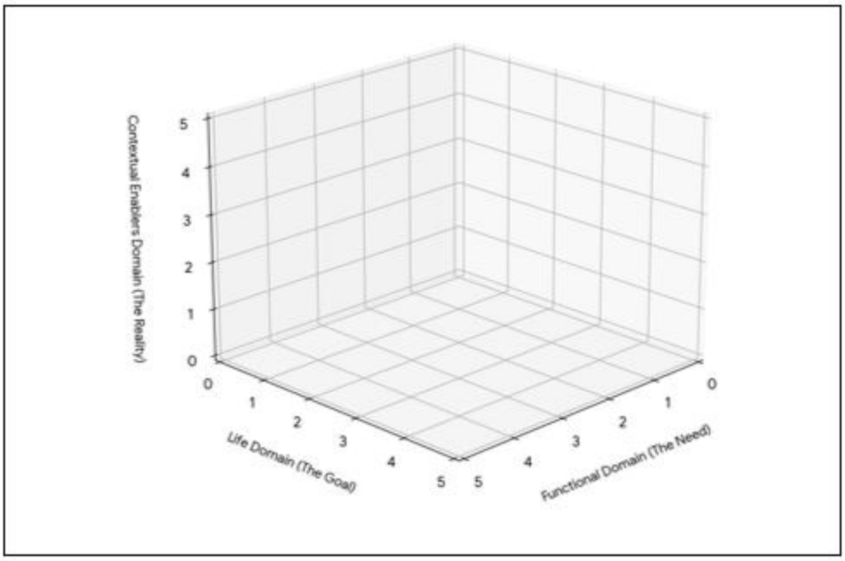

Figure 2. *Three-dimensional framework for people with disabilities in Malaysian community-based rehabilitation.*

Decision zones practical application

The core mapping principle dictates that the three-dimensional coordinates from the Functional, Life, and Contextual domains are used in combination to identify the most appropriate category of AI or Assistive Technology (AI/AT) and its corresponding delivery pathway. The systematic literature review indicates that while the Functional Domain score identifies the specific task-based need such as motor support, cognitive aid, the Life and Contextual axis values critically weight or moderate this decision, determining the feasibility, intensity, and sustainability of an intervention. Hence, to make this 3D model practical for on-the-ground implementation by CBR staff, the complex coordinate space can be partitioned into simplified Decision Zones as shown in *Figure 3*. These zones function as a traffic light system for intervention planning: (1) Green Zone: Proceed to trial. The user's profile and environment are a strong match for the proposed technology; (2) Amber Zone: Pilot with safeguards. The intervention may be viable but has identified risks such as borderline contextual score which requires extra monitoring, support, or a phased rollout; (3) Red Zone: Not currently feasible. The intervention is highly likely to fail. An alternative pathway must be chosen, such as focusing on context-building before reconsidering the technology.

eISSN: 2716-6481
https://doi.org/10.55197/qjssh.v7i1.947

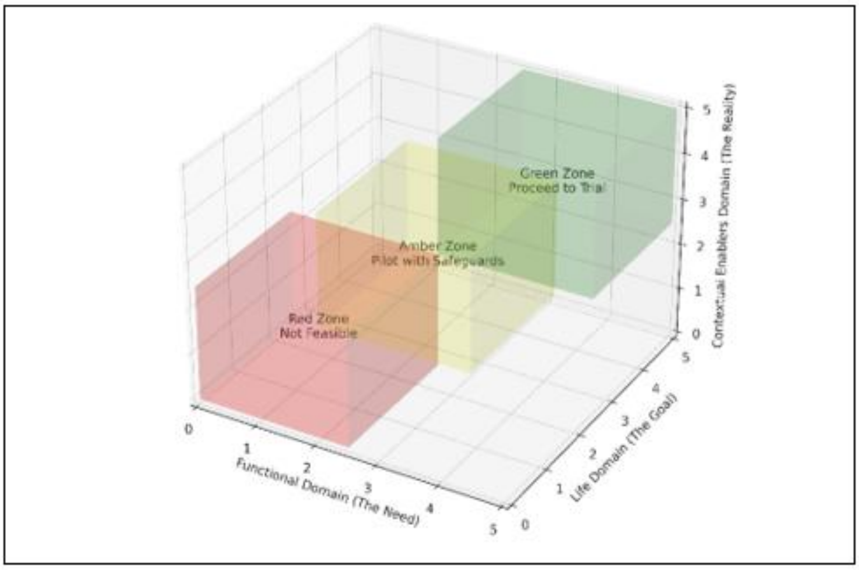

Figure 3. *Three-Dimensional Framework Decision Zones for on-the-ground implementation by the Malaysian Community-based Rehabilitation.*

These zone thresholds are not arbitrary but are derived directly from feasibility and effectiveness evidence in the literature. For example, clinical trials for home-based robotics and complex AI monitoring consistently show that these interventions only yield sustained benefits when contextual enablers are robust and life goals are strong (Bonanno et al., 2023; Campagnini et al., 2022). Therefore, to be placed in the Green Zone for such an advanced solution, a user would need to meet a minimum threshold on all three axes (e.g., Functional ≥ 3 AND Life ≥ 3 AND Context ≥ 3). If the user's coordinates fall below this threshold, the recommendation would shift to the Amber (pilot) or Red (recommend alternative) zone (Xue et al., 2025; Mennella et al., 2023).

Conclusion

The three-axis diagnostic model translates systematic review evidence into a pragmatic decision instrument that enables community-based rehabilitation practitioners to position each person with a disability as a coordinate in a functional-life-context “diagnostic space,” thereby ensuring that AI or assistive-technology (AI/AT) choices are task-aligned, goal-driven, and implementation-feasible (Mohammad Namdar et al., 2025; Kaelin et al., 2021). By embedding functional assessment, explicit life or participation goal negotiation, and a rapid context-enablers scan, the model operationalizes best practices from rehabilitation, implementation science, and AI-in-health literature to reduce mismatches between technological capability and real-world needs, limit harms from inappropriate deployments, and prioritize scalable, low-risk pathways when contextual enablers are weak (Shmonin et al., 2023; Noukpo et al., 2022). The model’s use in CBR is supported by evidence that community programs can deliver effective, low-cost rehabilitation and participation gains in low-income and middle-income settings when family and community supports are mobilized and when interventions are evaluated with mixed, participatory methods which conditions that the diagnostic tool explicitly incorporates through caregiver training and staged piloting (Trani et al., 2022; 2021; Bokalial et al., 2020). Operational deployment should follow a

eISSN: 2716-6481
https://doi.org/10.55197/qjssh.v7i1.947

staged validation and implementation agenda such as rapid pilots with mixed-methods evaluation, iterative refinement with persons with disabilities and community rehabilitation workers, and integration with CBR monitoring frameworks and national AI/AT procurement and governance pathways to enable scale while preserving safety and fairness (Epalte et al., 2023; Tofani et al., 2021). Finally, the model anticipates resilience needs and the diversity of low-income and middle-income country realities by recommending low-bandwidth, offline, or community-hub delivery options and explicit attention to financing and workforce development so that AI becomes an enabler of inclusion rather than an additional barrier to access (Ahmed et al., 2024; Lugo-Agudelo et al., 2021). Grounded in the systematic literature review (SLR) and CBR evidence base, the three-axis diagnostic space offers a defensible, practice-oriented route to match persons with disabilities to AI solutions that are medically appropriate, person-centred, and practically deployable within Malaysia's community rehabilitation ecosystem.

Acknowledgement

This research is self-funded.

Conflict of interest

The authors confirm that there is no conflict of interest involve with any parties in this research study.

REFERENCES

[1] Adenan, N.D., Abdullah, N., Mohamad Said, N.S., Abdul Manaf, S.M., Mohd Zahari, A.S. (2023): Community-Based Rehabilitation: An Overview of Organisational Practices. – International Journal of Academic Research in Business and Social Sciences 13(11): 2758-2767.

[2] Ahmed, A.N., Nuri, R.P., Xu, X., Balakrishna, V., Sebeh, A., Maholo, C., Aldersey, H.M. (2024): Community-based rehabilitation/community based inclusive development functioning during the COVID-19 pandemic: A secondary analysis of qualitative data. – PLOS ONE 19(1): 1-12.

[3] Alouthah, M.G.S., Alshammari, M.F.N., Alsaadi, H.F.F., Alshammari, S.N.K., Alonayzan, H.H.M., Alenezi, T.S.S., Alotaibi, M.S.A., Alghanim, H.A., Alharbi, T.A., Albarrak, O.S.M., Alshammari, M.A., Altheyab, S.A., Almutrfy, M.A., Alharbi, M.S.S., Alharbi, S.S. (2024): Advanced technologies in rehabilitation programs: Role of AI in diagnosis-an updated review. – International Journal of Health Sciences 8(S1): 1588-1604.

[4] Amdan, M.A., Janius, N., Jasman, M.N.B., Kasdiah, M.A.H.B. (2024): Advancement of ai-tools in learning for technical vocational education and training (TVET) in Malaysia (empowering students and tutor). – International Journal of Science and Research Archive 12(1): 2061-2068.

[5] Apostolidis, K., Kokkotis, C., Moustakidis, S., Karakasis, E., Sakellari, P., Koutra, C., Tsiptsios, D., Karatzetzou, S., Vadikolias, K., Aggelousis, N. (2023): Machine Learning Algorithms for the Prediction of Language and Cognition Rehabilitation Outcomes of Post-stroke Patients: A Scoping Review. – Human-Centric Intelligent Systems 4(1): 147-160.

[6] Arends, B.K.O., McCormick, J.M., Van Der Harst, P., Heus, P., Van Es, R. (2025): Barriers, facilitators and strategies for the implementation of artificial intelligence-based electrocardiogram interpretation: A mixed-methods study. – European Journal of Clinical Investigation 55(S1): 1-10.
[7] Arifin, N.N.M., Hassan, A.C., Musman, M., Nik Wil, N.J. (2025): Breaking Barriers: Empowering Special Needs Accountants in Malaysia through Artificial Intelligence and Assistive Technology. – Information Management and Business Review 17(3(I)S): 326-334.
[8] Banyai, A.D., Brişan, C. (2024): Robotics in Physical Rehabilitation: Systematic Review. – Healthcare 12(17): 1-17.
[9] Bokalial, D., Hossain, Md. F., Kumar, N.S.S., Bajracharya, S. (2020): Effectiveness of Community-Based Rehabilitation on the lives of Parents of Children with Cerebral Palsy: A Mixed Method Study in Karnataka, India. – Disability, CBR & Inclusive Development 31(3): 23-45.
[10] Boltaboyeva, A., Baigarayeva, Z., Imanbek, B., Ozhikenov, K., Getahun, A.J., Aidarova, T., Karymsakova, N. (2025): A Review of Innovative Medical Rehabilitation Systems with Scalable AI-Assisted Platforms for Sensor-Based Recovery Monitoring. – Applied Sciences 15(12): 1-28.
[11] Bonanno, L., Cannuli, A., Pignolo, L., Marino, S., Quartarone, A., Calabrò, R.S., Cerasa, A. (2023): Neural Plasticity Changes Induced by Motor Robotic Rehabilitation in Stroke Patients: The Contribution of Functional Neuroimaging. – Bioengineering 10(8): 1-22.
[12] Bulan, P.M.P., Kuizon, D.A.Y., Casaña, R.S.E., Fuentes, C.G., Pestaño, N.Y., Suerte, J.R.O. (2025): A Scoping Review on Artificial Intelligence in Occupational Therapy. – Occupational Therapy Journal of Research 15p.
[13] Bzikowska-Jura, A., Sobieraj, P., Raciborski, F. (2021): Low Comparability of Nutrition-Related Mobile Apps against the Polish Reference Method-A Validity Study. – Nutrients 13(8): 1-18.
[14] Campagnini, S., Arienti, C., Patrini, M., Liuzzi, P., Mannini, A., Carrozza, M.C. (2022): Machine learning methods for functional recovery prediction and prognosis in post-stroke rehabilitation: A systematic review. – Journal of NeuroEngineering and Rehabilitation 19(1): 1-22.
[15] Chin, C.S., Piragasam, G.A. (2021): Adoption of DETB with SRP amongst VIP at Tertiary Institutions in Malaysia. – International Journal of Academic Research in Progressive Education and Development 10(2): 24-34.
[16] Chomutare, T., Tejedor, M., Svenning, T.O., Marco-Ruiz, L., Tayefi, M., Lind, K., Godtliebsen, F., Moen, A., Ismail, L., Makhlysheva, A., Ngo, P.D. (2022): Artificial Intelligence Implementation in Healthcare: A Theory-Based Scoping Review of Barriers and Facilitators. – International Journal of Environmental Research and Public Health 19(23): 1-18.
[17] Damschroder, L.J., Reardon, C.M., Widerquist, M.A.O., Lowery, J. (2022): The updated Consolidated Framework for Implementation Research based on user feedback. – Implementation Science 17(1): 1-16.
[18] De Freitas, M.P., Piai, V.A., Farias, R.H., Fernandes, A.M.R., De Moraes Rossetto, A.G., Leithardt, V.R.Q. (2022): Artificial Intelligence of Things Applied to Assistive Technology: A Systematic Literature Review. – Sensors 22(21): 1-20.
[19] Denecke, K., Baudoin, C.R. (2022): A Review of Artificial Intelligence and Robotics in Transformed Health Ecosystems. – Frontiers in Medicine 9: 1-13.
[20] Epalte, K., Grjadovojs, A., Bērziņa, G. (2023): Use of the Digital Assistant Vigo in the Home Environment for Stroke Recovery: Focus Group Discussion With Specialists Working in Neurorehabilitation. – JMIR Rehabilitation and Assistive Technologies 10: 1-14.

[21] Eziamaka, N.V., Odonkor, T.N., Akinsulire, A.A. (2024): AI-Driven accessibility: Transformative software solutions for empowering individuals with disabilities. – International Journal of Applied Research in Social Sciences 6(8): 1612-1641.
[22] Fujimori, R., Liu, K., Soeno, S., Naraba, H., Ogura, K., Hara, K., Sonoo, T., Ogura, T., Nakamura, K., Goto, T. (2022): Acceptance, Barriers, and Facilitators to Implementing Artificial Intelligence–Based Decision Support Systems in Emergency Departments: Quantitative and Qualitative Evaluation. – JMIR Formative Research 6(6): 1-12.
[23] Guo, A., Kamar, E., Vaughan, J.W., Wallach, H., Morris, M.R. (2020): Toward Fairness in Ai for People with Disabilities: A Research Roadmap. – ACM SIGACCESS Accessibility and Computing 125: 1p.
[24] Guo, K., Orban, M., Lu, J., Al-Quraishi, M.S., Yang, H., Elsamanty, M. (2023): Empowering Hand Rehabilitation with AI-Powered Gesture Recognition: A Study of an sEMG-Based System. – Bioengineering 10(5): 1-18.
[25] Hakiki, B., Donnini, I., Romoli, A.M., Draghi, F., Maccanti, D., Grippo, A., Scarpino, M., Maiorelli, A., Sterpu, R., Atzori, T., Mannini, A. (2022): Clinical, Neurophysiological, and Genetic Predictors of Recovery in Patients With Severe Acquired Brain Injuries (PRABI): A Study Protocol for a Longitudinal Observational Study. – Frontiers in Neurology 13: 1-12.
[26] Hasan, H., Abdul Aziz, A.F., Aljunid, S.M. (2021): Parents' and caregivers' satisfaction with community-based rehabilitation (CBR) services for children with disability in east coast states in Peninsular Malaysia. – Health & Social Care in the Community 29(1): 215-226.
[27] Hurtubise, K., Gaboury, I., Berbari, J., Battista, M.C., Schuster, T., Phoenix, M., Rosenbaum, P., De Camargo, O.K., Lovo, S., Pritchard-Wiart, L., Zwicker, J.G. (2022): Training Intervention and Program of Support for Fostering the Adoption of Family-Centered Telehealth in Pediatric Rehabilitation: Protocol for a Multimethod, Prospective, Hybrid Type 3 Implementation-Effectiveness Study. – JMIR Research Protocols 11(10): 1-16.
[28] Iberahim, M.A.I., Shamsuddin, S.N.W., Makhtar, M., El-Ebiary, Y.A.B. (2024): Enhancement Of Finger State Progress Model for Markerless Virtual Fine Motor Stroke Rehabilitation. – Nanotechnology Perceptions 20(S14): 1025-1034.
[29] Istiyati, S., Marmoah, S., Poerwanti, J.I.S., Supianto, Sukarno, Mahfud, H. (2023): Comparative Study of Education for Children with Special Needs in Malaysia and Indonesian Primary School. – Jurnal Penelitian Pendidikan IPA 9(10): 7903-7908.
[30] Jabatan Kebajikan Masyarakat (JKM) (2023): Laporan Statistik Tahunan PDK 2022. – Jabatan Kebajikan Masyarakat, Kementerian Pembangunan Wanita, Keluarga dan Masyarakat 270p.
[31] Jeter, R., Greenfield, R., Housley, S.N., Belykh, I. (2024): Classifying Residual Stroke Severity Using Robotics-Assisted Stroke Rehabilitation: Machine Learning Approach. – JMIR Biomedical Engineering 9: 1-15.
[32] Kaelin, V.C., Valizadeh, M., Salgado, Z., Parde, N., Khetani, M.A. (2021): Artificial Intelligence in Rehabilitation Targeting the Participation of Children and Youth With Disabilities: Scoping Review. – Journal of Medical Internet Research 23(11): 1-17.
[33] Kamrozzaman, N.A., Sabtu, S.A., Xiu Jie, A.L., Md Nayan, N.S. (2025): Barriers to Artificial Intelligence Adoption in the Malaysian Virtual Assistant Industry: A Mixed-Methods Study. – International Journal of Research and Innovation in Social Science IX(V): 3722-3732.
[34] Kim, J., Kim, S., Rhee, J., Lee, Y., Park, J. (2024): Exploring Information Accessibility Needs for Individuals with Visual Impairments in Digital Sophistication: Focusing on Welfare Center, Enterprise, and Government Policy. – Korean Society for Rehabilitation of Persons with Disabilities 28(4): 99-129.
[35] Koshy, D.I., Koshy, D., Joseph, K.V. (2025): Trauma Care Provision in Malaysia: Challenges, Strengths, and Strategic Priorities for System Reform. – Cureus 6p.

eISSN: 2716-6481
https://doi.org/10.55197/qjssh.v7i1.947

[36] Latif, G., Brahim, G.B., Abdelhamid, S.E., Alghazo, R., Alhabib, G., Alnujaidi, K. (2023): Learning at Your Fingertips: An Innovative IoT-Based AI-Powered Braille Learning System. – Applied System Innovation 6(5): 1-18.
[37] Liscano, Y., Bernal, L.M., Díaz Vallejo, J.A. (2025): Effectiveness of AI-Assisted Digital Therapies for Post-Stroke Aphasia Rehabilitation: A Systematic Review. – Brain Sciences 15(9): 1-20.
[38] Lourenço, J.W., Jesus, P.A.C.D., Lourenço, F., Canciglieri Junior, O., Schaefer, J.L. (2025): A Systematic Review on Assistive Technology Terminologies, Concepts, and Definitions. – Technologies 13(8): 1-20.
[39] Lugo-Agudelo, L., Sarmiento, K., Brunal, M., Correa, J., Borrero, A., Franco, L., Ianini, R., Lis, P., Vélez, C., Lugo, D., Gutenbrunner, C. (2021): Adaptations for rehabilitation services during the COVID-19 pandemic proposed by scientific organizations and rehabilitation professionals. – Journal of Rehabilitation Medicine 53(9): 1-10.
[40] Manirajee, L., Hanis Shariff, S.Q., Mohd Rashid, S.M. (2024): Assistive Technology for Visually Impaired Individuals: A Systematic Literature Review (SLR). – International Journal of Academic Research in Business and Social Sciences 14(2): 596-611.
[41] Matheny, M.E., Whicher, D., Thadaney Israni, S. (2020): Artificial Intelligence in Health Care: A Report From the National Academy of Medicine. – JAMA 323(6): 509-510.
[42] Mennella, C., Maniscalco, U., De Pietro, G., Esposito, M. (2023): The Role of Artificial Intelligence in Future Rehabilitation Services: A Systematic Literature Review. – IEEE Access 11: 11024-11043.
[43] Mohammad Namdar, M., Lowery Wilson, M., Murtonen, K.P., Aartolahti, E., Oduor, M., Korniloff, K. (2025): How AI-Based Digital Rehabilitation Improves End-User Adherence: Rapid Review. – JMIR Rehabilitation and Assistive Technologies 12: 1-13.
[44] Newman-Griffis, D.R., Desmet, B., Zirikly, A., Tamang, S., Chang, C.H. (2023): Editorial: Artificial intelligence for human function and disability. – Frontiers in Digital Health 5: 1-3.
[45] Noukpo, S.I., Kossi, O., Tedesco Triccas, L., Adoukonou, T., Feys, P. (2022): Content and Effectiveness of Community-Based Rehabilitation on Quality of Life in People Post Stroke: A Systematic Review with Meta-Analysis. – Disability, CBR & Inclusive Development 33(2): 345-345.
[46] Pancholi, S., Wachs, J.P., Duerstock, B.S. (2024): Use of Artificial Intelligence Techniques to Assist Individuals with Physical Disabilities. – Annual Review of Biomedical Engineering 26(1): 1-24.
[47] Rehman, I.U., Sobnath, D., Nasralla, M.M., Winnett, M., Anwar, A., Asif, W., Sherazi, H.H.R. (2021): Features of Mobile Apps for People with Autism in a Post COVID-19 Scenario: Current Status and Recommendations for Apps Using AI. – Diagnostics 11(10): 1-20.
[48] Rowland, S.P., Fitzgerald, J.E., Holme, T., Powell, J., McGregor, A. (2020): What is the clinical value of mHealth for patients? – NPJ Digital Medicine 3(1): 1-6.
[49] Sangers, T.E., Nijsten, T., Wakkee, M. (2021): Mobile health skin cancer risk assessment campaign using artificial intelligence on a population-wide scale: A retrospective cohort analysis. – Journal of the European Academy of Dermatology and Venereology 35(11): 772-774.
[50] Shmonin, A.A., Maltseva, M.N., Soloveva, L.N., Melnikova, E.V. (2023): Comparison of multidisciplinary use of the International Classification of Functioning (ICF) in paper and electronic forms for patients with acute stroke. – Regional Blood Circulation and Microcirculation 22(2): 44-50.
[51] Shukla, K. (2022): Access to assistive technology for people with visual impairment. – IHOPE Journal of Ophthalmology 1: 79-85.
[52] Smith, P., Smith, L. (2021): Artificial intelligence and disability: Too much promise, yet too little substance? – AI and Ethics 1(1): 81-86.

[53] Soares, A.N., Benetti, M. (2025): Low-Cost Assistive Technology at the Cross-Cut of Education and Health. – Revista de Gestão Social e Ambiental 19(5): 1-16.

[54] Tofani, M., Esposito, G., Berardi, A., Galeoto, G., Iorio, S., Marceca, M. (2021): Community-Based Rehabilitation Indicators: Validation and Preliminary Evidence for Disability in Italy. – International Journal of Environmental Research and Public Health 18(21): 1-10.

[55] Trani, J.F., Pitzer, K.A., Vasquez Escallon, J., Bakhshi, P. (2022): Access to Services from Persons with Disabilities in Afghanistan: Is Community Based Rehabilitation Making a Difference? – International Journal of Environmental Research and Public Health 19(10): 1-26.

[56] Trani, J.F., Vasquez-Escallon, J., Bakhshi, P. (2021): The impact of a community based rehabilitation program in Afghanistan: A longitudinal analysis using propensity score matching and difference in difference analysis. – Conflict and Health 15(1): 1-21.

[57] Umucu, E. (2025): Artificial Intelligence and Health Equity for People with Disabilities: An Integrated Framework for Disability-Inclusive AI Design. – INQUIRY: The Journal of Health Care Organization, Provision, and Financing 62: 1-6.

[58] Valentine, A.Z., Hall, S.S., Young, E., Brown, B.J., Groom, M.J., Hollis, C., Hall, C.L. (2021): Implementation of Telehealth Services to Assess, Monitor, and Treat Neurodevelopmental Disorders: Systematic Review. – Journal of Medical Internet Research 23(1): 1-14.

[59] Vélez-Guerrero, M.A., Callejas-Cuervo, M., Mazzoleni, S. (2021): Artificial Intelligence-Based Wearable Robotic Exoskeletons for Upper Limb Rehabilitation: A Review. – Sensors 21(6): 1-29.

[60] Vogan, A.A., Alnajjar, F., Gochoo, M., Khalid, S. (2020): Robots, AI, and Cognitive Training in an Era of Mass Age-Related Cognitive Decline: A Systematic Review. – IEEE Access 8: 18284-18304.

[61] Wang, X., Wang, B., Tew, W.Y., Yang, X., Xu, X., Gao, Y., Chen, Y., Yam, M.F. (2025): Exploring mHealth interventions for medication management: A scoping review of digital tools, implementation barriers, and patient outcomes. – PeerJ Computer Science 11: 1-34.

[62] Wiljer, D., Salhia, M., Dolatabadi, E., Dhalla, A., Gillan, C., Al-Mouaswas, D., Jackson, E., Waldorf, J., Mattson, J., Clare, M., Lalani, N., Charow, R., Balakumar, S., Younus, S., Jeyakumar, T., Peteanu, W., Tavares, W. (2021): Accelerating the Appropriate Adoption of Artificial Intelligence in Health Care: Protocol for a Multistepped Approach. – JMIR Research Protocols 10(10): 1-14.

[63] World Health Organization and the United Nations Children’s Fund (UNICEF) (2022): Global report on assistive technology. – UNICEF 7p.

[64] Xue, W., Duan, Ai., Zhao, Y., Zuo, H., Isleem, H.F. (2025): AI-enabled multimodal monitoring for enhanced safety and functional recovery in elderly and post-stroke care: A mixed-methods study. – DIGITAL HEALTH 11: 1-34.

[65] Yunus, F.W., Ahmad Ridhuwan, N.F., Romli, M.H. (2022): The Perception of Allied Health Professionals on Occupational Therapy. – Occupational Therapy International 8p.

[66] Zaidi, M.F.A. (2025): Understanding AI Ecosystem towards Sustainability in Malaysia. – Global Conference on Business and Social Sciences Proceeding 17(1): 69-69.

[67] Zainal, A.Z., Zainuddin, S.Z. (2020): Technology adoption in Malaysian schools: An analysis of national ICT in education policy initiatives. – Digital Education Review 37: 172-194.

[68] Zdravkova, K., Krasniqi, V., Dalipi, F., Ferati, M. (2022): Cutting-edge communication and learning assistive technologies for disabled children: An artificial intelligence perspective. – Frontiers in Artificial Intelligence 5: 1-14.

[69] Ziebland, S., Hyde, E., Powell, J. (2021): Power, paradox and pessimism: On the unintended consequences of digital health technologies in primary care. – Social Science & Medicine 289: 1-24.

eISSN: 2716-6481
https://doi.org/10.55197/qjssh.v7i1.947