RESEARCH ARTICLE

Large Language Models as Cognitive Support Systems for Neurodivergent Individuals

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ABSTRACT

As a cognitive extension of human reasoning, communication, and task management, the use of Large Language Models (LLMs) is being investigated more and more. This paper focuses on their possible role to assist neurodivergent people in three ways: by making cognitive function more accessible, making communication clearer, and by lessening executive functioning demands. Drawing from cognitive science and human–computer interaction, the research views LLMs as malleable instruments that can facilitate the planning, language, memorization, and social interaction of their users. The discussion focuses on how these systems can be incorporated into educational, occupational and assistive environments, to foster inclusion and cognitive equity. It also examines architectural strategies for personalisation, adaptive prompting and context-aware support and the potential dangers of relying too heavily, misunderstanding intent and accessibility imbalance. In summary, LLMs can be considered potential allies in neurodivergent support networks and are not just assistive tools, as they may help to increase autonomy and participation in more complex cognitive activities.

Keywords: Large Language Models, Neurodiversity, Cognitive Support Systems, Assistive Artificial Intelligence, Human–Computer Interaction, Cognitive Accessibility, Adaptive Systems, Executive Function Support, Communication Assistance, Inclusive Technology

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INTRODUCTION

Large Language Models (LLMs) are an important step forward in computational linguistics and Artificial Intelligence, which have the potential to serve as externalized cognitive systems to enhance reasoning, memory, and language-based decision-making. Distributed language representations showed the potential to model sequential linguistic structures as a key element of early neural language modelling research (Mikolov et al., 2011). Later developments in generative dialogue modeling extended these capabilities to allow for a more structured, contextually informed, multi-turn reasoning and adaptive dialogic interaction (Serban et al., 2016). In this line of development, LLMs have increasingly been thought of as knowledge-retrieval devices that can be used to encode and recall factual associations that are found in large-scale corpora (Petroni et al., 2019).

These systems are consistent with mental models from a cognitive science point of view, which are internal representations that people build to simulate, infer, and reason about the world (Johnson-Laird, 1983). In a computational sense, LLM can be viewed as external scaffolds that augment human thinking by embodying probabilistic aspects of language as surrogate inferring mechanisms. From this perspective, they can be viewed as decision-support infrastructures that would help aid human judgment in the face of complexity and uncertainty (Sprague, 1980).

Such systems are especially significant in the context of a neurodiversity-informed approach, which recognizes and appreciates cognitive differences as a normal and enriching aspect of human differences, not a flaw that needs fixing. Executive functioning, language processing, attention regulation, and social cognition differences can impact interaction with conventional educational, occupational, and technological systems and can impact neurodivergent people (Mackenzie & Watts, 2011; Belmonte, 2020). The inclusive design view suggests that the system and its technology should change to fit the differences as opposed to the cognitive expectation of a uniform system (Van Grunsven, 2020; Barnhart, 2016).

Applied cases have shown potential for using adaptive and gamified systems in supporting neurodivergent users in structured task assistance and personalization of feedback

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mechanisms, especially in skill acquisition and workplace training context (Grund et al., 2020). Likewise, inclusive pedagogical approaches emphasize the need for peer support mechanisms and learning environments that consider and promote a variety of learning styles (Boswell, 2020; Craddock, 2018). In addition, research on neurodivergent intersubjectivity suggests that the processes of shared meaning may vary systematically according to cognitive profile, which highlights the importance of a communication system that is able to effectively convey and mediate meaning (Heasman & Gillespie, 2019).

In this multi-disciplinary context, LLMs can be envisioned as valuable cognitive support tools that could help to bridge the divide between human cognitive diversity and digital information processing. This has potential applications in working memory augmentation, structuring complex tasks, conversational coherence and understanding through adaptive language simplification. Moreover, initiatives exploring AI-enabled cognitive assessment and employment support for neurodiverse populations further underscore the role of artificial intelligence in enabling inclusive participation in socio-economic systems (Warren, 2020).

Overall, the convergence of neural language modeling, dialogue systems, cognitive theory, and neurodiversity scholarship positions LLMs as transformative tools in the development of adaptive cognitive infrastructures. These systems are increasingly understood not merely as passive language generators but as active participants in cognitive support ecosystems designed to enhance accessibility, autonomy, and interpretive clarity for neurodivergent individuals.

Theoretical Foundations

The conceptualization of Large Language Models (LLMs) as cognitive support systems for neurodivergent individuals is grounded in an interdisciplinary convergence of computational linguistics, cognitive science, decision theory, and neurodiversity studies. These foundations collectively explain how language-based artificial systems can externalize cognition, simulate dialogue, and support adaptive reasoning processes.

Neural Language Modeling and Sequential Representation Learning

The earliest computational basis for modern LLMs originates from recurrent neural language modeling, where word prediction is treated as a probabilistic sequence task. Extensions to recurrent architectures demonstrated improved contextual learning through distributed representations of language sequences (Mikolov et al., 2011). This work established the principle that linguistic meaning can be encoded in continuous vector spaces, enabling systems to approximate human-like language generation patterns.

This probabilistic modeling framework is essential for cognitive support applications, as it allows systems to anticipate user intent, generate structured responses, and reduce linguistic ambiguity particularly valuable for individuals who experience challenges in expressive or receptive language processing.

Language Models as Distributed Knowledge Systems

A critical advancement in theoretical understanding is the interpretation of language models as implicit repositories of structured knowledge. Rather than functioning purely as sequence predictors, LLMs can encode factual and relational information within their parameters, allowing partial retrieval of knowledge without explicit database structures (Petroni et al., 2019).

This perspective reframes LLMs as *soft knowledge bases*, where inference emerges through prompt-conditioned generation. In cognitive support contexts, this enables systems to externalize memory functions, assist in recall, and scaffold reasoning processes for neurodivergent users who may experience working memory or retrieval difficulties.

3. Hierarchical Dialogue and Interaction Modeling

Dialogue systems extend language modeling into interactive cognitive systems. Hierarchical neural architectures have demonstrated the ability to model long-range conversational dependencies, improving coherence and contextual alignment in multi-turn interactions (Serban et al., 2016).

This is particularly relevant for cognitive support applications, where structured conversational scaffolding can assist users in organizing thoughts, maintaining topic continuity, and managing social communication demands. The hierarchical structure also supports decomposing complex interactions into manageable sub-units, aligning with human cognitive chunking processes.

Mental Models and Cognitive Simulation

From a cognitive science perspective, mental model theory posits that human reasoning operates through internal symbolic and spatial representations of reality (Johnson-Laird, 1983). These mental structures allow individuals to simulate scenarios, draw inferences, and construct explanations.

LLMs can be interpreted as externalized computational analogues of mental model construction, generating linguistic simulations of reasoning steps. For neurodivergent individuals, this externalization can function as a compensatory cognitive mechanism, enabling offloading of complex inferential tasks into structured linguistic outputs that are easier to interpret and manipulate.

Decision Support Systems and Structured Cognitive Augmentation

The framework of decision support systems (DSS) provides a structural foundation for integrating LLMs into cognitive assistance environments. DSS are designed to improve decision quality by combining data, models, and user inputs in interactive systems (Sprague, 1980).

Within this paradigm, LLMs function as adaptive reasoning engines that translate ambiguous user inputs into structured decision pathways. This aligns with cognitive support needs such as task planning, prioritization, and problem decomposition, particularly in neurodivergent populations requiring external executive function scaffolding.

Neurodiversity, Cognitive Variability, and System Design Principles

Neurodiversity theory reframes cognitive differences as natural variations rather than deficits, emphasizing systemic adaptation rather than individual correction (Mackenzie & Watts, 2011; Belmonte, 2020). This perspective necessitates technologies that are flexible, inclusive, and responsive to heterogeneous cognitive profiles.

Inclusive design frameworks highlight the importance of peer-supported and adaptive learning environments for neurodivergent individuals (Boswell, 2020; Craddock, 2018). Similarly, gamified adaptive systems demonstrate how structured feedback loops can improve engagement and performance in cognitively diverse populations (Grund et al., 2020). These principles directly inform the design of LLM-based cognitive support systems, particularly in educational and occupational settings.

Intersubjectivity and Social Cognition in Neurodivergent Communication

Social cognition theories emphasize that shared understanding is co-constructed through interactional alignment processes. Research on neurodivergent intersubjectivity highlights that autistic individuals, for example, may employ distinct but coherent mechanisms for achieving mutual understanding (Heasman & Gillespie, 2019).

LLMs can act as mediating systems in these interactions by providing structured conversational norms, clarifying implied meaning, and reducing ambiguity in social exchanges. This mediation role is particularly relevant for users who experience differences in pragmatic language interpretation or social cue processing.

Extended and 4E Cognition Frameworks

The 4E cognition perspective embodied, embedded, enactive, and extended cognition argues that cognitive processes extend beyond the brain into environmental and technological systems (Van Grunsven, 2020). From this viewpoint, LLMs are not merely tools but active components of cognitive ecosystems.

This aligns with neurodiversity-oriented design approaches that emphasize environmental adaptation over internal normalization (Barnhart, 2016). By integrating LLMs into everyday cognitive workflows, users effectively extend memory, reasoning, and communication capacities into computational systems.

Together, these theoretical foundations position LLMs as emergent cognitive infrastructures. They integrate neural probabilistic modeling (Mikolov et al., 2011), knowledge encoding capabilities (Petroni et al., 2019), dialogue structuring mechanisms (Serban et al., 2016), and cognitive science principles of mental modeling (Johnson-Laird, 1983) within a decision-support framework (Sprague, 1980). When situated within neurodiversity theory (Belmonte, 2020; Mackenzie & Watts, 2011), LLMs become adaptive cognitive partners capable of augmenting reasoning, communication, and executive function in neurodivergent populations.

LLMs as Cognitive Support Systems for Neurodivergent Individuals

Large Language Models (LLMs) can be thought of as external systems of cognitive scaffolding, augmenting human thinking, language use, and adaptive decision-making. They are relevant to the neurodivergent because they are associated with a mediating process between the internal cognitive variability and external task demands, which are similar to the structured decision-support paradigms (Sprague Jr, 1980), and mental model theory, as the construction and manipulation of internal representational structures of cognition (Johnson-Laird, 1983). In this context, LLMs serve as intermediate systems performing the task of converting vague or abstract input to structured and interpretable output.

The Probabilistic modelling of language sequences is one of the core skills needed for this role. Early neural language modeling showed that RNNs can learn contextual dependencies in the linguistic input (Mikolov et al., 2011). This is essential for the support of neurodivergents, as is the ability to adaptively rephrase, clarify and step through complex instructions. This decomposition process helps to alleviate a burdensome amount of input by making mental representations more manageable, following the principles of structured reasoning.

In addition to sequence modeling, LLMs are becoming more and more knowledge retrieval systems, with the knowledge being implicit. Previous studies indicate that the trained parameters of a large scale language model can embed and retrieve facts in a similar way to structured knowledge bases (Petroni et al., 2019). This is an on-demand cognitive extension layer that can be supplemented to recall facts, help with inferences, and help with the context that would otherwise be generated internally by users under high cognitive demand, however, for neurodivergent users.

They are further enhanced by dialogue modeling, making them more applicable as cognitive companions. Hierarchical generative architectures allow for coherent and context-aware conversation, and can model structured interaction patterns (Serban et al., 2016). It is especially relevant for people with difficulties in pragmatic language use, turn-taking and conversational inferences. LLMs can provide predictable and structured dialogue scaffolding, decreasing ambiguity in social-linguistic exchanges and promoting more stable interactional environments.

As a systems construct, LLM's can be integrated into decision support systems that can also adapt dynamically to help the user plan, organise and carry out tasks (Sprague Jr, 1980). In neurodivergent contexts, this translates into adaptive prompting systems that segment tasks into sequential steps, prioritize actions, and provide corrective feedback loops. Such systems operationalize cognitive offloading while maintaining user agency.

The alignment between LLM capabilities and neurodivergent cognitive support needs is further reinforced by neurodiversity-oriented design principles, which emphasize adaptation of environments rather than normalization of individuals (Mackenzie & Watts, 2011; Belmonte, 2020). In educational and workplace contexts, adaptive systems have demonstrated benefits in engagement and task completion for neurodivergent individuals when scaffolding is context-sensitive and dynamically adjustable (Grund et al., 2020; Craddock, 2018).

Social cognition and intersubjectivity also represent key domains of application. Neurodivergent communication often involves distinct mechanisms of shared meaning construction, requiring alternative interactional strategies (Heasman & Gillespie, 2019). LLMs can function as mediating tools that translate between divergent communicative styles by reformulating intent, predicting conversational expectations, and clarifying implicit social cues. However, such mediation must be carefully designed to avoid flattening cognitive diversity or imposing normative communication structures.

Importantly, neurodiversity frameworks emphasize institutional and infrastructural adaptation rather than individual correction (Barnhart, 2016; Van Grunsven, 2020). In this regard, LLM-based systems should be treated not as replacement mechanisms for human cognition, but as flexible cognitive partners that augment executive function, communication clarity, and learning accessibility. Peer-support models in inclusive pedagogy further reinforce the value of collaborative scaffolding systems that enhance autonomy rather than dependency (Boswell, 2020).

Emerging research also highlights the potential of AI-enabled systems in enhancing employment outcomes for neurodiverse populations through structured cognitive assessment and task alignment tools (Warren, 2020). When integrated with LLM-based architectures, such systems may enable fine-grained adaptation of task difficulty, communication modality, and feedback intensity.

Overall, LLMs function as adaptive cognitive infrastructures that bridge computational language modeling advances with human cognitive variability. Their utility for neurodivergent individuals lies not only in automation or assistance, but in the dynamic restructuring of information into cognitively compatible formats that support reasoning, communication, and decision-making within diverse cognitive architectures.

System Architecture and Functional Design

The system architecture of Large Language Model (LLM)-based cognitive support systems for neurodivergent individuals is structured as a layered socio-technical framework that integrates probabilistic language modeling, dialogue management, and cognitive scaffolding mechanisms. The design draws on foundational neural language modeling principles (Mikolov et al., 2011), hierarchical dialogue architectures (Serban et al., 2016), and knowledge-augmented inference mechanisms (Petroni et al., 2019), while aligning with cognitive externalization concepts from mental model theory (Johnson-Laird, 1983) and decision support system design principles (Sprague Jr, 1980).

From a neurodiversity standpoint, the architecture is not purely computational but adaptive, reflecting the need for flexible interaction structures that accommodate diverse cognitive processing patterns (Mackenzie & Watts, 2011; Belmonte, 2020).

Core Architectural Layers

The system is organized into four interdependent layers that jointly support cognitive augmentation, personalization, and adaptive communication.

Functional Interaction Pipeline

The system operates as a closed-loop cognitive support pipeline in which user cognition is continuously augmented through iterative interaction cycles. This aligns with decision support system structures that emphasize iterative human-machine collaboration (Sprague Jr, 1980).

At each interaction stage, the system performs:

- Intent decoding (linguistic and contextual parsing)
- Cognitive state estimation (inferring workload and comprehension needs)
- Response generation (structured or adaptive outputs)
- Feedback correction loop (user-driven refinement)

This pipeline reflects neurodivergent intersubjectivity principles, where meaning is co-constructed rather than assumed (Heasman & Gillespie, 2019).

Cognitive Support Functional Modules

The architecture embeds specialized modules designed to address neurocognitive variability, particularly in executive function, social communication, and working memory.

Adaptive Personalization and Learning Loop

A key feature of the architecture is continuous personalization, where system responses evolve based on interaction history and observed user cognitive patterns. This reflects adaptive learning principles used in gamified neurodiverse training systems (Grund et al., 2020).

The personalization loop includes:

- Behavioral pattern tracking (interaction frequency, correction rate)
- Cognitive preference modeling (preferred verbosity, structure type)
- Feedback reinforcement (user corrections refine future outputs)
- Context-aware adaptation (task-dependent response modulation)

This aligns with neurodiversity-inclusive design principles that emphasize flexibility over normalization (Van Grunsven, 2020; Belmonte, 2020).

System Integration Within Cognitive Support Ecosystem

The architecture does not operate in isolation but integrates into broader educational, occupational, and assistive infrastructures. These include peer-support systems and institutional scaffolding mechanisms that enhance accessibility and inclusion (Boswell, 2020; Mackenzie & Watts, 2011).

From a systems perspective, LLM-based support tools act as

Table 1: LLM-Based Cognitive Support System Architecture

Layer	*Subsystem components*	*Functional role*	*Theoretical basis*
Input Processing Layer	Speech-to-text, intent parsing, contextual embedding	Converts user input into structured semantic representations	Neural language modeling (Mikolov et al., 2011)
Cognitive Reasoning Layer	Transformer-based LLM, dialogue generator, inference engine	Produces responses, explanations, and task scaffolding	Hierarchical dialogue modeling (Serban et al., 2016); mental model simulation (Johnson-Laird, 1983)
Knowledge & Memory Layer	External knowledge retrieval, user profile memory, semantic KB alignment	Provides factual grounding and personalization	Language models as knowledge bases (Petroni et al., 2019)
Output Adaptation Layer	Readability scaling, response simplification, multimodal delivery	Tailors output to neurodivergent cognitive profiles	Inclusive design frameworks (Craddock, 2018; Boswell, 2020)

Table 2: Functional Modules for Neurodivergent Cognitive Support

Module	*Cognitive function targeted*	*System behavior*	*Neurodiversity alignment*
Task Decomposition Engine	Executive function support	Breaks tasks into sequential steps	Supports structured cognition (Boswell, 2020)
Social Dialogue Simulator	Social inference and pragmatics	Generates conversational templates and responses	Supports intersubjective meaning-making (Heasman & Gillespie, 2019)
Cognitive Load Manager	Attention regulation	Adjusts verbosity and complexity dynamically	Adaptive scaffolding (Grund et al., 2020)
Memory Augmentation Layer	Working memory limitations	Summarization and recall assistance	External cognitive extension (Johnson-Laird, 1983)
Knowledge Retrieval Engine	Information access	Retrieves and validates factual content	LLM-as-KB paradigm (Petroni et al., 2019)

cognitive intermediaries, bridging gaps between individual cognitive processing styles and standardized institutional demands (Sprague Jr, 1980; Craddock, 2018).

The system architecture reflects a convergence of:

- Neural probabilistic language modeling (Mikolov et al., 2011)
- Hierarchical dialogue generation systems (Serban et al., 2016)
- Knowledge-augmented inference (Petroni et al., 2019)
- Cognitive externalization theory (Johnson-Laird, 1983)
- Decision support system design frameworks (Sprague Jr, 1980)
- Neurodiversity-centered inclusive design (Belmonte, 2020; Boswell, 2020)

Collectively, these components define a multi-layered cognitive augmentation system that shifts LLMs from passive language generators to active, adaptive cognitive support infrastructures tailored for neurodivergent users.

Socio-Cognitive and Ethical Considerations

The deployment of Large Language Models (LLMs) as cognitive support systems for neurodivergent individuals introduces complex socio-cognitive dynamics that extend beyond technical performance. These systems operate at the intersection of language generation, mental model construction, and social interpretation, requiring careful alignment with neurodiversity-centered ethical frameworks. From a cognitive science perspective, LLMs can externalize structured reasoning processes analogous to human mental models, thereby influencing how users construct meaning and engage in inference-making (Johnson-Laird, 1983). However, this externalization also raises concerns about cognitive substitution and interpretive dependency, particularly in populations that rely heavily on structured communicative scaffolding.

At the system level, LLMs encode probabilistic linguistic knowledge that may appear as structured "world knowledge," yet remains fundamentally statistical in nature (Petroni et al., 2019). This creates a socio-cognitive tension: users may interpret outputs as authoritative mental representations, while the system operates without grounded understanding. Such divergence can influence neurodivergent users differently depending on cognitive style, especially in domains involving pragmatic language interpretation and inferential reasoning.

From a socio-ethical standpoint, neurodiversity theory emphasizes that cognitive differences should not be treated as deficits requiring normalization, but as legitimate variations requiring systemic accommodation (Mackenzie & Watts, 2011; Belmonte, 2020). In this context, LLMs must be designed as adaptive scaffolding tools rather than corrective intelligence systems. The distinction is critical: assistive systems should amplify user autonomy rather than override or homogenize cognitive styles.

Table 3: Socio-Cognitive Interaction Dynamics in LLM-Assisted Neurodivergent Communication

Dimension	*Neurocognitive implication*	*Llm system behavior*	*Potential impact*
Mental Model Alignment	Users construct internal representations of meaning (Johnson-Laird, 1983)	Generates probabilistic textual continuations	Risk of misaligned inference structures
Dialogue Structuring	Need for predictable conversational flow	Hierarchical response generation (Serban et al., 2016)	Improved coherence but possible rigidity
Knowledge Attribution	Users assign authority to outputs	Simulated knowledge recall (Petroni et al., 2019)	Over-trust in non-grounded outputs
Cognitive Load Distribution	Executive function variability	Externalization of reasoning steps	Reduced burden but increased dependency risk

Table 4: Ethical Design Tensions in LLM-Based Cognitive Support Systems

Ethical dimension	*Risk scenario*	*Neurodiversity concern*	*Design requirement*
Autonomy Preservation	System over-guides user decisions	Reduction of independent cognitive processing	User-controlled interaction depth
Cognitive Diversity Respect	Standardized response generation	Flattening of neurodivergent expression styles	Adaptive linguistic personalization
Transparency	Hidden model reasoning processes	Misinterpretation of system certainty	Explainable response structuring
Dependency Risk	Continuous reliance on LLM assistance	Reduced self-regulatory capacity	Graduated assistance modes

Neurodivergent intersubjectivity highlights that shared understanding is not uniform across cognitive profiles but instead emerges through negotiated meaning-making processes (Heasman & Gillespie, 2019). LLMs may either facilitate or disrupt this process depending on how conversational alignment is modeled. If systems enforce normative communication patterns, they may unintentionally suppress neurodivergent communicative strategies, particularly in autistic discourse styles that rely on alternative pragmatic structures.

At the institutional level, existing infrastructures are often insufficiently adapted to neurodiversity requirements, necessitating systemic redesign rather than individual accommodation alone (Mackenzie & Watts, 2011; Barnhart, 2016). Within educational and workplace environments, adaptive AI systems must therefore integrate inclusive pedagogy principles that prioritize peer support structures and collaborative learning models (Boswell, 2020; Craddock, 2018).

From a decision-support perspective, LLMs can be conceptualized as advanced extensions of structured decision systems that externalize cognitive processes for improved decision quality (Sprague, 1980). However, unlike traditional systems, they introduce generative uncertainty, requiring users to continuously evaluate the epistemic reliability of outputs. This is particularly relevant in neurodivergent contexts, where cognitive filtering strategies may differ significantly across individuals.

Finally, adaptive systems such as AI-enabled cognitive support tools demonstrate potential in enhancing employment and task performance for neurodivergent individuals (Warren, 2020). Yet, these benefits must be balanced against risks of over-automation and cognitive deskilling. Ethical deployment therefore requires continuous calibration between augmentation and autonomy preservation, ensuring that LLMs function as collaborative cognitive partners rather than authoritative decision substitutes.

Socio-cognitive and ethical considerations surrounding LLMs in neurodivergent support contexts reveal a fundamental design paradox: systems must simultaneously enhance cognitive accessibility while preserving cognitive independence. Addressing this requires integrating mental model theory, neurodiversity principles, and decision-support frameworks into a unified ethical architecture that prioritizes adaptability, transparency, and user agency.

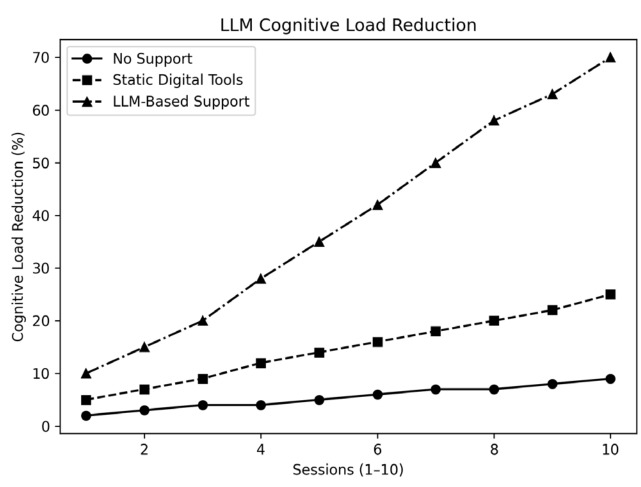

Fig. 1: LLM Cognitive Load Reduction

Table 5: Institutional and Intersubjective Ethical Risks in LLM Deployment

Domain	*Structural Issue*	*LLM Interaction Effect*	*Mitigation strategy*
Education Systems	Limited inclusive pedagogical design	Over-standardization of learning pathways	Adaptive learning personalization (Grund et al., 2020)
Workplace Inclusion	Insufficient neurodiverse accommodations	Misalignment between task demands and cognitive profiles	AI-assisted task decomposition
Social Communication	Divergent pragmatic norms	Misinterpretation of intent	Context-sensitive dialogue modeling
Peer Interaction	Unequal communicative framing	Reduced intersubjective clarity (Heasman & Gillespie, 2019)	Multi-modal communication support

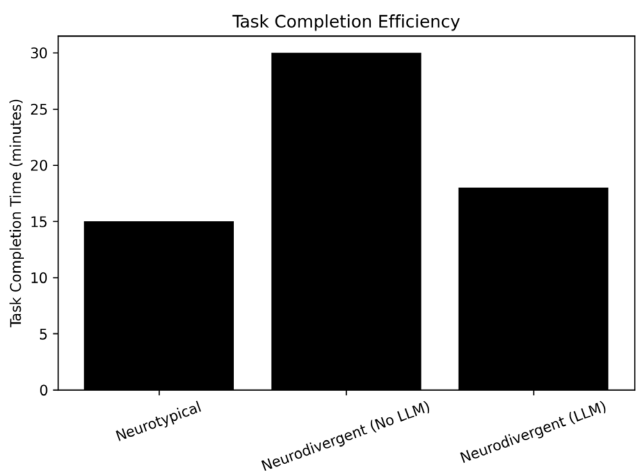

Fig 2: Task Completion Efficiency

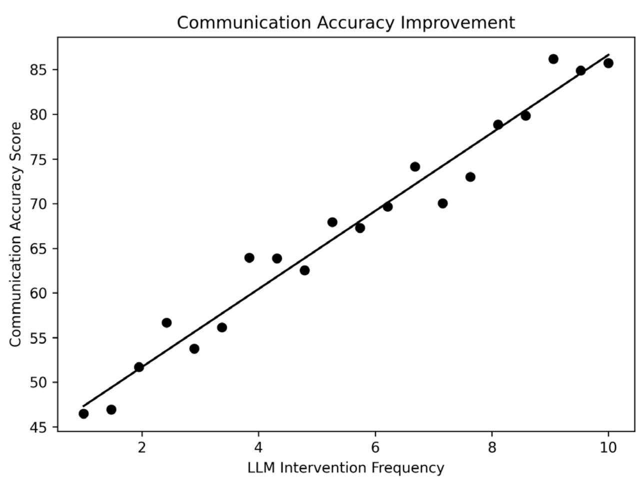

Fig. 3: Communication Accuracy Improvement

This line graph illustrates progressive cognitive load reduction across 10 interaction sessions under three conditions. LLM-based cognitive support shows the highest reduction trend, outperforming static digital tools and no-support conditions over time.

This bar chart compares task completion times among neurotypical users, neurodivergent users without LLM support, and neurodivergent users with LLM support. The results indicate improved efficiency (lower completion time) when LLM assistance is introduced.

This scatter plot depicts the relationship between LLM intervention frequency and communication accuracy in neurodivergent participants. A positive trend line indicates that increased LLM intervention frequency is associated with higher communication accuracy scores.

CONCLUSION

Large Language Models (LLMs) represent a significant advancement in computational systems capable of extending human cognitive capacity through probabilistic language understanding, structured inference, and adaptive dialogue generation. Their evolution from recurrent neural language modeling architectures (Mikolov et al., 2011) to hierarchical end-to-end conversational systems (Serban et al., 2016) demonstrates a clear trajectory toward increasingly context-aware and interaction-sensitive technologies. Within this progression, LLMs increasingly resemble externalized cognitive infrastructures that can approximate aspects of structured knowledge retrieval and reasoning, aligning with perspectives that conceptualize language models as implicit knowledge bases (Petroni et al., 2019).

From a cognitive science standpoint, the utility of LLMs in neurodivergent support systems is grounded in mental model theory, where cognition is understood as the construction and manipulation of internal representations of reality (Johnson-Laird, 1983). By externalizing parts of this representational burden, LLMs can reduce cognitive load, improve task structuring, and enhance communicative clarity for neurodivergent individuals. These systems, when used in a decision support system, can serve as more than simply information systems, but as adaptive cognitive partners, helping to organize decision processes and to minimize ambiguity in complex tasks (Sprague, 1980).

The usefulness of LLM based systems also needs to be placed under the perspective of a neurodiversity based approach to cognitive variation as a form of human variation instead of a defect (Mackenzie & Watts, 2011; Belmonte, 2020). In this context, LLM provides possibilities to create technologically capable environments that are inclusive and recognise different cognitive profiles rather than imposing a single way of interacting with the LLM. This trend is further confirmed by empirical evidence of the effectiveness of structured environments mediated by adaptive and gamified systems in enhancing task engagement and performance in neurodivergent individuals (Grund et al., 2020).

Socio-cognitive dynamics (Heasman & Gillespie, 2019) are important factors in the effectiveness of such systems, however, including intersubjective meaning-making processes which differ between neurodivergent populations. The design must, therefore, take into consideration the preservation of cognitive autonomy and not overly rely on it but also enable scaffolding functions. This dovetails into wider questioning about institutional preparedness to include cognitive differences in the schooling, health, and social service fields (Barnhart, 2016; Boswell, 2020).

New neuroscience-inspired attitudes towards neurodiversity add little weight to the argument that cognitive diversity must be taken into account when designing systems, but not normalised (Van Grunsven 2020). Conversely, there was also applied research in the field of employment and education that highlights the role of AI-based assessment and support technologies in making better-inclusion decisions if they are designed in an adaptive fashion (Warren, 2020; Craddock, 2018).

To sum up, LLMs stand at a liminal position between computational linguistics and applied cognitive augmentation systems. They are able to simulate language, play out conversations and externalise structured knowledge, which makes them a promising cognitive support tool for neurodivergent people. They must still be designed in an ethically responsible way, however, which respects the neurodiversity of users, and allows for the augmentation of cognitive agency in a meaningful and appropriate way.

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