Exploring Cognitive Development with Recursive Quantitative Analysis: A First Simulated Look

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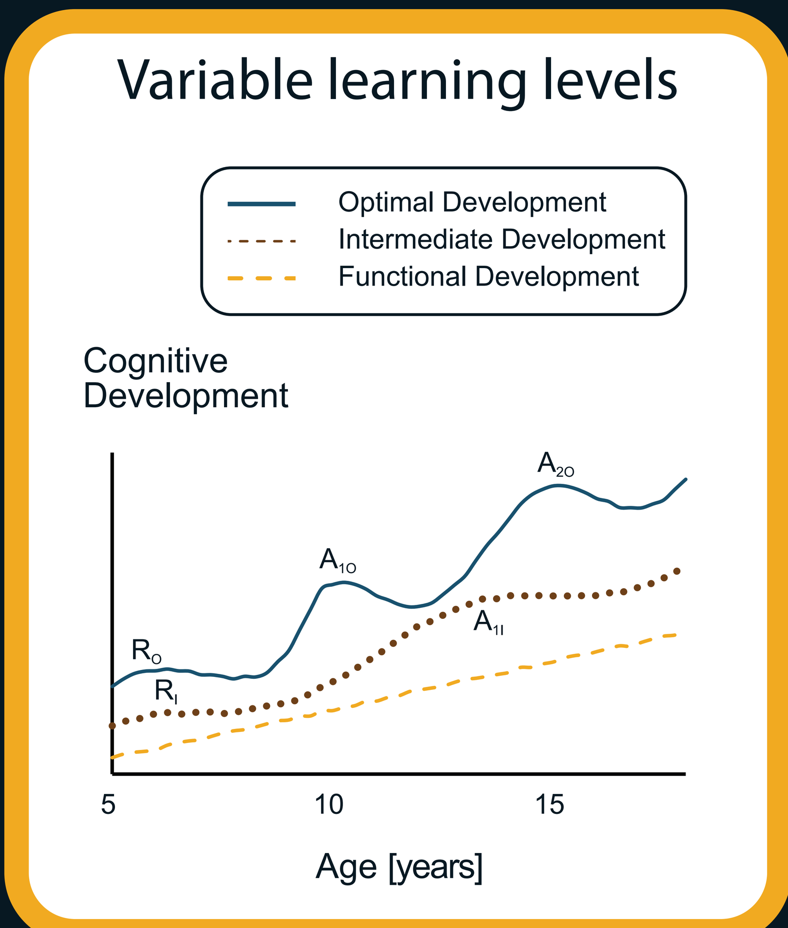

Figure 1: As derived from Fischer[3], cognitive development under optimal and increasingly sub-optimal (intermediate and functional, respectively) conditions. R_*, A_{1*} and A_{2*} represent the onset of representational systems, single abstractions and abstract mappings cognitive capacities for Optimal and Intermediate conditions, respectively. Although these particular milestones are achieved for functional development, stages are not clearly marked by a spike in capacity corresponding to onset.

Issue Explored

The utilization of Recursive Quantitative Analysis (RQA) on a model of cognitive development to assess the potential of RQA as an analytic tool to be used for in-situ educational research.

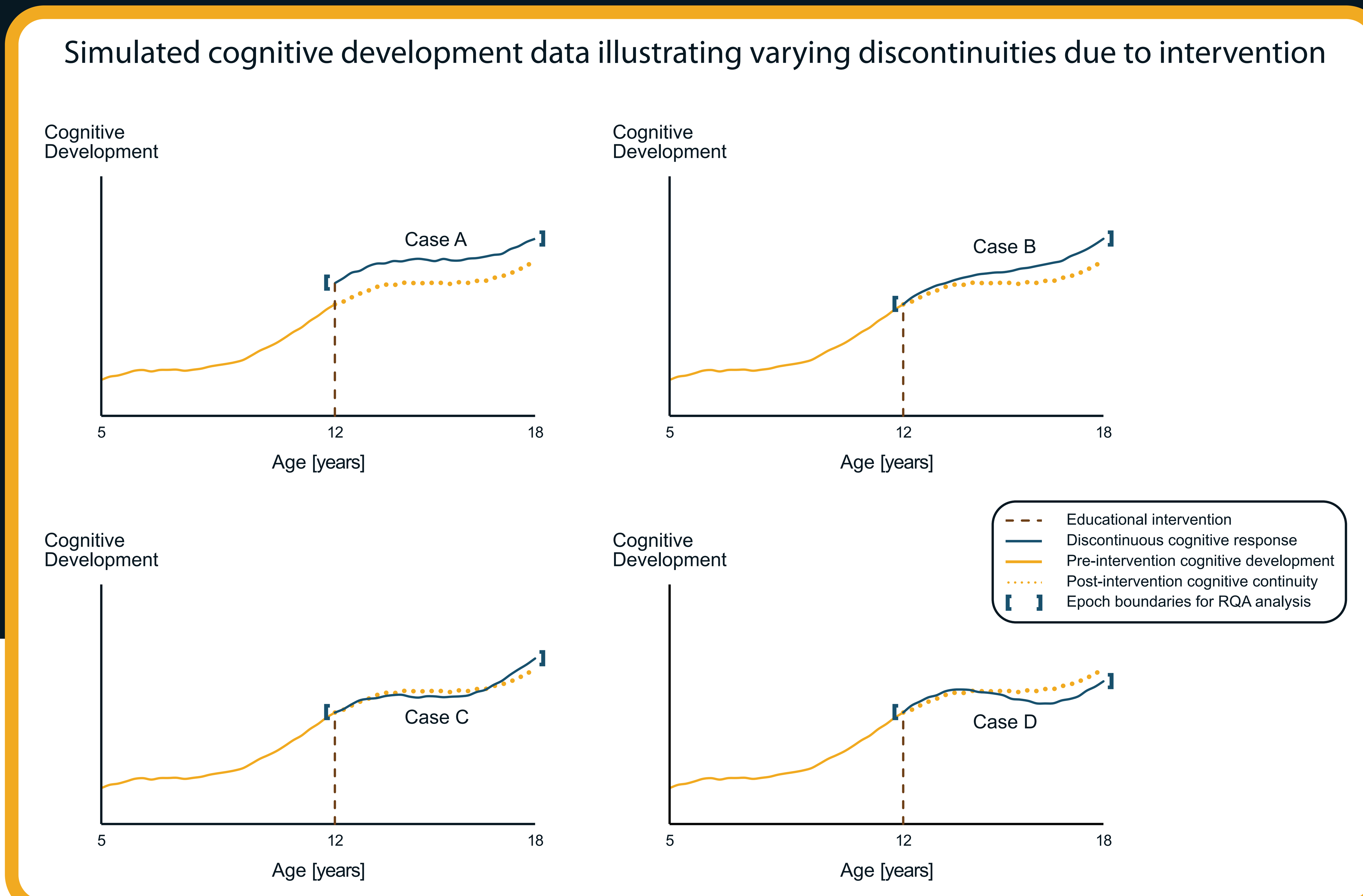

Figure 2: Simulations of discontinuities in intermediate cognitive function generated by educational intervention at age 12. Case A – Jump Discontinuity, Case B – Slope Discontinuity, Case C – Periodic Discontinuity, Case D – Amplitude Discontinuity, Case E – Continuity.

Introduction

Learning is complex, dynamic and characterized by:[5]

- Non-linearity and self-organization
- Superpositioning
- Multi-layering and multi-scaling

It is delineated by discontinuous stages[3]. These stages are well defined under optimal learning conditions, and become less pronounced as learners deviate from optimal conditions (figure 1)[2].

Education is changing and requires empirical research to support ongoing theoretical work.[1] Historically, educational research has utilized a variety of designs requiring linearizing assumptions[4]. Non-linear methods are required in analysis to preserve the complexity of the system and supply construct validity to findings.

Recursive Quantitative Analysis (RQA) has recently emerged from the field of dynamical systems theory[7]. RQA embeds time series data into higher dimensional space and quantifies the relationship between recursive points[4]. RQA holds strong potential for the field of education because:

- Maintenance of the sequential ordering of time series data
- Demonstrated success on analysis of similarly related input signals.

Keywords

Cognitive Development, Complex Dynamical Systems, Learning, Modelling, Recursive Quantitative Analysis, RQA, Simulation

Methods

Key characteristics of the relationship between cognitive function and age [years] (optimal conditions):[2, 3]

1. Maxima at each of 6, 10 and 15 years
2. Drift
3. Aperiodicity
4. Random error

The relationship was modelled and transformed to sub-optimal levels (figure 1). Cognitive development was studied using RQA under a variety of conditions used to simulate discontinuities in learning due to educational intervention at age 12 (figure 2). RQA variables were computed for each of the test cases (figure 2) utilizing parameters defined in Table 1.

Parameter	Value
Delay	1
Embedding Dimension	10
Data Range	All
Normalization	Euclidean
Rescaling	None
Radius	1
Line	2

Table 1: Analysis parameters for RQA.

Observations

Type of discontinuity influenced the recurrence variables (table 2). Taken together, the results show large variation in:

1. Deterministic structure (larger %determ values describe increasing periodicity)
2. Stability (larger lmax values depict greater stability)
3. Homogeneity (trend deviations from zero indicate increasing heterogeneity) of cognitive development

Large variations in recurrence were observed between the discontinuous cases (A-D) and the pre-intervention data and smaller variations were observed between the continuous case (E) and the pre-intervention data.

Variable	Case A - Jump	Case B - Slope	Case C - Period	Case D - Amplitude	Case E - Cont'd	Pre-Intervention
# recurs	71	468	2840	12527	1870	1580
#lines	20	92	524	642	383	308
%recur	0.04%	0.27%	1.63%	7.18%	1.07%	0.66%
%determ	70.42%	88.03%	88.38%	99.46%	87.65%	89.37%
lmax	5	17	20	493	15	28
entropy	1.19	2.88	3.12	4.77	2.87	2.98
trend	-0.22	-1.67	-8.38	-29.34	-5.82	-3.31
%laminar	2.82%	39.74%	41.06%	99.70%	18.77%	37.15%
vmax	2	8	14	84	6	8
traptime	2.00	2.86	2.76	14.54	2.21	2.56

Table 2: Results of RQA analysis on each of 5 simulations and including pre-intervention simulation data.

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Conclusions

Results of this theoretical experiment support that RQA provides an effective tool in analysis of learning. The implication of this finding to the field of MBE is that in-situ research can benefit from the use of RQA in assessment of the efficacy of educational interventions. Prior to implementing RQA, methodological work is still required, including sensitivity and specificity testing in addition to the development of strategies to periodically measure cognitive development.

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