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Title: CRDE Study Shows 18% Skill-Based Learning Loss for Indian Students Returning after COVID-19 School Closures

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"Measuring learning loss is a critical first step towards mitigating its consequences. It is vital that countries invest in assessing the magnitude of such losses to implement the appropriate remedial measures." (Silvia Montoya, quoted in UNESCO, 2021)

State of Indian education post-COVID

Education has been severely disrupted in India by the COVID-19 pandemic. As of 2 March 2021, Indian students experienced, on average, 146 full days of school closure and an additional 89 days of partial school closure. (UNICEF, 2021) This white paper reports the results of the first of a projected series of studies conducted in collaboration with CRDE schools to assess whether and to what extent learning losses were experienced by Indian students. Educational data from previous natural disasters indicate that learning gaps inevitably arise and that those gaps are likely to widen, not close, after students return to school. (Andrabi *et al.*, 2020; Kim, 2010; Brock, 2013; De Vreyer *et al.*, 2014; Di Pietro, 2018; Binde, 2018; Gibbs *et al.*, 2019; Thamtanajit, 2020; Sapkota & Neupane, 2021) The results we obtained in India are consistent with the outcomes consistently observed globally over several decades of academic research. The results of the present study support the following conclusions:

1) School closures due to COVID-19 have unambiguously **harmed Indian students**;
2) Students currently manifest an **18% drop in skill-based learning**; and,
3) Learning losses can be **expected to worsen** unless schools introduce teaching interventions significantly different from those previously attempted.

To understand the Indian educational landscape post-COVID, the landmark study by Andrabi *et al.* of the educational impact of the 2005 Kashmir earthquake is directly relevant. In 2005, an earthquake measuring 7.6 on the Richter scale struck the Pakistani-administered region of Azad Kashmir, killing over 80,000 people—nearly a quarter of whom were children. Due to the disaster, students in affected areas missed an average of 14 weeks of school. Four years after the earthquake, researchers discovered:

- Student test scores were an average of **1.5 to 2 years behind** their peers;

- School closure accounted for only 10% of the loss in test scores; **90% of learning losses occurred after students returned to school**; and,
- If these deficits continued into adulthood, affected students were projected to **lose 15% of their lifetime earnings**.

When schools reopened after the earthquake, educators naturally wished to help their students catch up. In practice, this took the form of teachers covering more material in less time. Cramming became the *de facto* norm. This had disastrous consequences, especially for students who were of average or below-average academic ability. Students who were able to keep up with the previous pace of delivery began to fall behind, and students who were already struggling with the curriculum prior to the earthquake quickly fell even further behind.

Whatever Indian educational policy makers may hope to the contrary, this appears to be exactly what is happening on the ground.

Measuring skill-based learning losses of Indian students

Because of their anticipated relevance to post-COVID teaching interventions, for our study we chose to focus on measuring 21st century skills. Sometimes called *life skills* or *employability skills*, 21st century skills include critical thinking skills, communication skills, and other soft skills essential for both the global economy and personal growth. Cultivation of 21st century skills has emerged as a central concern of ministries of education and global employers. These are the skills sought for during university admissions and job interviews, and personal mastery of 21st century skills significantly impacts professional advancement.

There are several different accounts of 21st century skills.[1] The schema we adopt here distinguishes 21st century skills into three categories:

1 Mapping between any of the better-known 21st century skills schemata is fairly straightforward, and in practice which scheme one adopts is largely a matter of convenience. Inter-translation is often a simple matter of nomenclature: *critical thinking skills* are sometimes called *analytical thinking skills* (as, e.g., in Singapore). For elucidation and justification of the account adopted here, see Mooney & Nowacki (2011) and Nowacki *et al.* (2009).

1. *Situational Intelligence* (SQ) — the skills and concepts needed to make good decisions in a changing world;
2. *Collaborative Intelligence* (CQ) — the skills and concepts needed to work with other people; and,
3. *Global Intelligence* (GQ) — the skills, concepts, and qualities needed to be an effective global citizen.

Measuring Situational Intelligence (SQ)

To measure SQ, we used the LogicMills MirMe SQ assessment, which is an online, validated, game-based psychometric assessment for 21st century skills. (Luan & Nowacki, 2021) The MirMe assessment for SQ consists of an abstract strategy game played three times and a 15-item yes/no survey. Upon completion, the system calculates an overall summative or holistic score for SQ. This summative score is calculated from three major components (called "SQ Categories"), each of which in turn is calculated from multiple sub-components (each of which in turn depends on various sub-sub-measures).

Table 1. Component measures of the MirMe SQ assessment.

SQ: skills we need to make good decisions in a changing world	
SQ Category	Components
Jump in and know where you are • Size up an environment • J – Score	• Identify and set goals • Prioritize needs • Evaluate options • Pursue multiple goals • Utilize resources efficiently • Select appropriate solutions among alternatives
Know what you can do • Identify options & plan ahead • K – Score	• Create opportunities • Make accurate predictions/forecasts • Create first-mover advantage/carve out a niche • Tackle problems before they arise
Do it and see if it works • Respond to feedback • D – Score	• Modify behaviour during competition • Prevent / block competition • Find new resources

As may be gathered from Table 1, MirMe is designed to measure SQ, understood as *the skills we need to make good decisions in a changing world*. The instrument's *SQ-Score* represents a holistic measure of this.

The MirMe SQ-Score is based, *inter alia*, upon results calculated for three distinct skill categories. The reasoning behind the categories is that, whenever somebody possesses situational intelligence, that individual displays three characteristics: First, one must be able to *Jump in and know where you are* ("J-Score"). That is, one must be able to size up an environment and quickly identify significant patterns and key drivers in that environment. Second, one should *Know what you can do* ("K-Score"). That is, one should be able to identify options and think ahead. Third, one must be able to *Do it and see if it works* ("D-Score"). This means that one is able to assimilate environmental feedback and adapt to it in a flexible manner. The overall SQ-score is (largely) determined by the participant's J-Score, K-Score, and D-Score.

Experiment

The CRDE test run is the first in a series of measurement studies. The plan is to eventually assess and monitor students aged 9-16 from 1,000 schools across the India. The test run involved 381 students randomly selected from 11 schools in three Indian states. This initial test run will be followed by a pilot phase involving 40,000 students, and then scaled up to a projected 4 lakh students. The ultimate objective of CRDE is to provide objective and timely feedback to educators and policymakers so that effective teaching interventions can be identified and subjected to continuous improvement.

Table 2 presents descriptive statistics for the experiment. There are two data sets compared: 381 randomly-selected students who participated in the CRDE test run in March 2022; and 2,363 Indian students (again, randomly selected) who took the MirMe assessment in 2018 and 2019 and who thus provide a pre-COVID in-country comparison. Both groups are roughly balanced between males and females. One notable difference is that the CRDE participants were 14 years old whereas the pre-COVID baseline students were 9 years old.

When interpreting the MirMe results, note that all SQ-scores are age-normed. This norming is based on more than 50,000 participants in validation studies conducted during MirMe's development. While the majority of the participants in these validation studies were drawn from Asia, there are representative samples from North America, Oceania, Europe, and the Middle East. MirMe scores therefore come reasonably close to exemplifying a global assessment standard for students with internet access pre-COVID.

Table 2. Descriptives for CRDE Test Run and India Pre-COVID-19 Baseline.

CRDE Test Run (Post-COVID-19)					
CRDE total # students CRDE avg age CRDE avg time taken	381 14 22.4 minutes	SQ score*	J score	K score	D score
High score		81	91	97	91
Low score		35	0	4	1
Mean score	Avg all-in	57	28	37	37
Drop (low) outliers (<15 raw)	Avg post drop	61	36	42	42
CRDE post drop	# dropped	88	117	67	59
CRDE post drop	% dropped	23%	31%	18%	15%
India Baseline (Pre-COVID-19)					
Baseline total # students Baseline avg age Baseline avg time taken	2363 9 20.9 minutes	SQ score*	J score	K score	D score
High score		86	96	97	96
Low score		37	0	1	0
Mean score baseline	Avg all-in	60	30	38	38
Drop (low) outliers (<15 raw)	Avg post drop	62	38	44	43
Baseline post drop	# droppped	187	667	399	418
Baseline post drop	% dropped	8%	28%	17%	18%
CRDE vs India Baseline (Pre-COVID-19)		SQ score*	J score	K score	D score
Loss % avg all-in vs base [=(CRDE-Base)/Base]		-5%	-8%	-4%	-3%
Loss % avg post-drop [=(CRDE-Base)/Base]		-2%	-5%	-4%	-2%

* Note: SQ scores are age-normed; J, K, and D are raw scores and are not age-normed.

In contrast with SQ-scores, the data reported for J-, K-, and D-scores are not age normed; rather, these three category measures may be treated as raw performance scores and hence may be directly compared across age groups. Older participants—at least through university the years—typically achieve higher raw performance scores than younger ones. Thus, for example, when age-norming is applied, a raw J-score that would receive an 'A' grade for a 9 year old might only merit a 'B' or 'C' for a 21 year old.

Inspection of the table reveals that the younger Indian students significantly out-performed their older post-COVID compatriots. The baseline students took less time to complete the MirMe assessment, and in every average measurement achieved higher scores than the CRDE students. This is especially striking in the case of the J-, K-, and D-scores, where for every directly-comparable raw score the 9 year old pre-COVID students outperformed the 14 year old post-COVID students. *Prima facie*, this is convincing evidence that COVID-19 has had a deleterious effect on Indian students.

To test whether the CRDE students might have had a disproportionate number of low outliers, we analysed the case where we dropped students who achieved a raw score of 15 or less. (This raw score represents a percentile raw score as measured against the 50,000 participants in the validation studies.) While doing so had the expected effect of raising average scores for both CRDE and the Indian baseline, the percentage of each sample dropped for J-, K-, and D-scores was similar. Due to age-norming, the gap between the percentage of participants who were dropped due to low SQ performance was significantly less for the baseline students: only 8% for the baseline compared to 23% for CRDE. Taken together, these results suggest that the explanation for the CRDE group under-performance is not due to an unusual number of low outliers but rather a consequence of a systematic drop in average performance across the board. Again, this is clear evidence that COVID-19 is responsible for skill-based learning losses in Indian students.

We turn now to a consideration of Table 3, which presents student performance broken down into quartiles. With age-norming, we expect to see SQ-scores describing a general bell shape, with most students falling into the two middle quartiles. The baseline SQ scores are high in this regard, with 77% of students in the 26–75 range. The CRDE group is likewise slightly on the high side, with 71%. The difference in SQ performance appears most clearly when we compare the extremes: the baseline has a significantly higher percent of its members in the top quartile than the CRDE sample (16% vs. 6%), and the baseline has a significantly lower percentage of its group in the bottom quartile than CRDE (8% vs. 23%).

Table 3. Quartile comparison before and after COVID-19 school closures.

CRDE Test Run (Post-COVID-19)								
QUARTILE DATA CRDE								
Quartile	SQ # students	SQ % students	J # students	J % students	K # students	K % students	D # students	D % students
Top 25 (76-100)	24	6%	9	2%	27	7%	16	4%
Next 25 (51-75)	107	28%	49	13%	81	21%	73	19%
Next 25 (26-50)	162	43%	115	30%	124	33%	171	45%
Bottom 25 (1-25)	88	23%	208	55%	149	39%	121	32%
Baseline for India (Pre-COVID-19)								
QUARTILE DATA BASELINE								
Quartile	SQ # students	SQ % students	J # students	J % students	K # students	K % students	D # students	D % students
Top 25 (76-100)	374	16%	75	4%	184	8%	131	6%
Next 25 (51-75)	1086	46%	360	16%	587	25%	474	21%
Next 25 (26-50)	716	31%	702	30%	694	30%	951	41%
Bottom 25 (1-25)	187	8%	1226	52%	898	39%	807	35%

Looking again at Table 3, we note that for J-, K-, and D-scores the younger baseline students have a higher percentage of students in the top two quartiles than the older CRDE students. This is despite applying precisely the same cut-offs to the raw scores for both samples. The bottom quartiles for J-, K-, and D-scores are very close in their representation. We interpret this as a signal that age-norming would be appropriate for the younger baseline group. (This is discussed below in relation to Table 4.) Once again, the data supports the conclusion that COVID-19 has had a negative effect on Indian students: we observe a general erosion of performance and evidence of skill-based learning losses.

In Table 4, we see the distribution of letter grades in each category for CRDE students. Note that, unlike the raw numerical scores, assignment of letter grades is age-normed. This age-norming of letter grades is done in comparison with the global benchmarks obtained pre-COVID during the validation studies for MirMe.

Inspection of Table 4 shows that the expected bell distribution does not apply. While the global sample follows a normal distribution, in every category the CRDE results are weighted toward the lower grades. Very few students achieve an 'A' grade in any of the components, and the most common grades are 'C' and 'D'. On the assumption that Indian students pre-COVID followed a distribution pattern similar to the global norm for 14 year olds, the data supports the conclusion that there has been an erosion of 21st century skills post-COVID.

Table 4. Distribution of MirMe letter grades for CRDE test run.

MirMe Letter Grades			
SQ-J-K-D	**Grade**	**# students**	**% students**
SQ	A	24	6%
	B	107	28%
	C	162	43%
	D	88	23%
J	A	2	1%
	B	81	21%
	C	90	24%
	D	208	55%
K	A	3	1%
	B	105	28%
	C	140	37%
	D	133	35%
D	A	1	0%
	B	118	31%
	C	110	29%
	D	152	40%

We now turn to assessing the magnitude of the negative impact of COVID-19. Our results are summarised in Table 5. We begin by explaining the meaning of the various columns in the table.

Each of MirMe's three categories is built up from subcomponents. As may be gathered from Table 1 above, there are six subcomponents for the J-score, four subcomponents to the K-score, and three subcomponents for the D-score. This is reflected in the '# Comps' column of Table 5.

MirMe reports the average (mean) raw score for all participants of the relevant pre-COVID global comparison group (i.e., participants who are 14 years old). From this, we calculate the expected summative score for subcomponents of our J-, K-, and D-scores. MirMe also reports the actual summative score for these subcomponents achieved by the CRDE test group. The results of these calculations are given in the 'Comps summative' column of Table 5.

To facilitate comparison among the three categories, we added the 'Comps Avg' column. This column reports the result of dividing the 'Comps summative' results by the number of subcomponents.

We then used two methods to triangulate the raw numerical J-, K-, and D-scores against global pre-COVID expectations. The first method involved comparing the expected summative score and actual summative score for the subcomponents of the J-, K-, and D-scores. We use the formula

(ActualScore – ExpectedScore) / ExpectedScore

to calculate the 'Gain/Loss via Avg' column.

The second method involved comparing the MirMe-generated final scores for each category (reported in the 'Score' column). These are all percentile calculations. In other words, MirMe pre-ranked the subcomponent scores of the pre-COVID global group into a baseline percentile list, and then identifies where the CRDE group should appear in that ranking. This allows us to calculate how CRDE students stand relative to the baseline 50th percentile using the formula

(ComponentScore – 50) / 50.

Results are given in the 'Gain / Loss % via %tile' column.

The last column of Table 5 reports the average of the preceding two columns, giving us a picture of where and to what degree Indian students experienced learning losses for the J-, K-, and D-categories. According to the schema for 21st century skills adopted here, students lost the most ground in their ability to size up an environment (J-score loss of 26%), followed by their ability to adapt to environmental circumstances (D-score loss of 16%), and experienced the least deterioration in their ability to plan ahead (K-score loss of 13%). When we average these category-based learning losses, **we arrive at a holistic score for the skill-based learning losses suffered by Indian students due to COVID: 18%.**

Table 5. Calculation of skill-based learning losses due to COVID-19.

CRDE Test-Run vs Global Baseline							
Performance reference	**Score**	**# Comps**	**Comps summative**	**Comps Avg**	**Gain / Loss % via Avg**	**Gain / Loss % via %tile**	**Gain / Loss Avg %**
Final SQ score	**57**						
Final J score	**34**	6					
Expected Sub-J score			276	46			
Actual Sub-J score			219	37			
DIFF +/-			57	10	**-21%**	**-32%**	**-26%**
Final K score	**41**	4					
Expected Sub-K score			188	47			
Actual Sub-K score			172	43			
DIFF +/-			16	4	**-9%**	**-18%**	**-13%**
Final D score	**38**	3					
Expected Sub-D score			137	46			
Actual Sub-D score			126	42			
DIFF +/-			11	4	**-8%**	**-24%**	**-16%**
					TOTAL ESTIMATED LOSS		**-18%**

We then wished to test whether our result of an 18% learning loss is in line with the amount of learning losses reported by other researchers investigating the impact of natural disasters. To do this, we built a simple model wherein the impact of skill-based learning losses compound with curriculum content learning losses over time. The model is given in Table 6.

In the model we assume that there is a relation between *know-that* (i.e., facts taught as part of the curriculum, such as the biological fact that there are three orders of mammals: placentals, marsupials, and monotremes), and *know-how* (i.e., skills developed via practice during student learning). The basic insight is that one can be more or less skilled as a learner, and that those who are skilled at learning will find it easier to master factual knowledge. For example, there are well-known techniques that, with practice, enable us to improve our ability to memorise and deliberately recall information.

To capture the notion of *know-that* in our model, we assume that students are expected to learn 100 new facts every year. (This can be thought of as 100% of the factual content of the yearly curriculum.) We also assume that an 18% loss of learning *know-how* results in an 18% drop in the quantity of facts a student can learn in a year. Thus, in Year 1, students master only 82 of the year's 100 new facts.

The trouble really begins in Year 2. Students are expected to learn another 100 facts, but those facts in turn have dependency conditions; learning one fact may require that one know a prior fact, or learning a new fact may presuppose an undeveloped skill. To include this feature, we treat the quantity of new facts a student can learn as a function of the number of facts learnt the previous year further discounted by the skill-based learning loss. So, as given in Table 6, in Year 2 a student would be expected to learn 67 (out of 100) new facts. This follows the formula

(#FactsLearntPrevYear x %LearntAfterLossInSkills) = #NewFactsLearntThisYear

hence,

(82 facts Y1) x (1 - .18 skill loss) = 67 facts Y2.

Table 6. Simple model for compounding learning losses.

CRDE MODEL PROJECTING SKILL-DERIVED LEARNING LOSSES IN INDIA						
COMPOUNDING LEARNING LOSSES (Highlight shows where > 1 year of learning lost)						
% Skill Loss	18%	**% Learnt**	82%			
# Items to Learn / Year	100					
Year	**1**	**2**	**3**	**4**	**5**	**6**
Cumulative # Items to Learn	100	200	300	400	500	600
# New Items Learnt in Year	82	67	55	45	37	30
Cumulative # Items Learnt	82	149	204	250	287	317
Cumulative % Items Learnt	82%	75%	68%	62%	57%	53%
Cumulative % Items Lost	-18%	-25%	-32%	-38%	-43%	-47%
Total # Lost Items	18	51	96	150	213	283

When we run the model, we find that at the end of Year 3 students have lost almost one full year (i.e., 96 out of a year's 100 facts) and that after Year 4 they have fallen 1.5 years (i.e., 150 facts) behind where they should be. This is very much in line with what happened after the 2005 Kashmir earthquake discussed earlier, where four years after the disaster students were an average of 1.5 to 2 years behind their peers in unaffected areas. Despite its simplicity, the model does support the overall reasonableness of the 18% figure for skill-based learning losses we calculated.

What is concerning about the model is that an 18% skill learning loss could well be a *conservative* estimate. Affected students in Kashmir missed approximately 14 weeks of school. In comparison, Indian students missed an average of 146 full days and 89 partial days due to COVID-19 school closures. (UNICEF, 2021) The 2005 Kashmir earthquake, while tragic, was limited to a relatively small geographical region. The impact of COVID-19, of course, is global. (See: Maldonado & De Witte, 2022; EEF, 2021; Hammerstein *et al.*, 2021; Engzell *et al.*, 2020; Dorn *et al.*, 2020a; Dorn et al., 2020b; Chen *et al.*, 2021.)

Concluding remarks and recommendations for educational policymakers

Looking forward, we recommend that assessment studies be conducted as soon as possible to establish a baseline for students returning to school. Given that skills take time to consolidate, it would be ideal to assess students every six months over a period of two years. This would support meaningful feedback on post-COVID teaching interventions, and give sufficient opportunity for educators and educational policymakers to introduce further pedagogical fine-tuning.

There is an important practical point here for educational policymakers. The hurdle CRDE hopes to overcome with its test run and follow-up studies is having people on the ground acknowledge that the damage is real. It is one thing for a school administrator to casually skim an academic article that claims 'this terrible thing will happen'; it is quite another to have it pointed out that 'this terrible thing has *already* happened to *your* students in *your* school–and it will continue to get worse if *you* don't do anything.'

As a recovery measure, CRDE is currently advocating that schools implement a targeted, skills-based post-COVID teaching intervention. Doubtless there are many good ways to solve the problem. The structure of the intervention CRDE advocates is described briefly in an Appendix to this white paper. From a policy perspective, it would be ideal to evaluate a number of teaching interventions. The takeaway for educational policymakers is that there must be some form of assessment and monitoring to track the efficacy of diverse interventions. Moreover, starting with assessment is likely to help with getting buy-in from educators. For this, CRDE has found MirMe to be an appropriate and useful instrument.

APPENDIX

Effective Post-COVID Teaching Intervention

High-level solution: M-T-M

Providing an abstract description of any successful post-COVID learning intervention is easy: Measure-Teach-Measure ('M-T-M'), and repeat as necessary. That is, one should:

1. **Measure** a salient 21st century skill;
2. **Teach** students, using an intervention that targets that skill; and,
3. **Measure** the target skill again to track learning progress.

It is hardly controversial to say that good teaching works like this. What should be noted, though, is that recommending an M-T-M approach comes with an easily-overlooked cost. Note that a significant body of research warns that most of the harm done happens *after* students return to school. Teachers compress material and accelerate the pace of delivery in an effort to help students catch up. Insofar as M-T-M represents best practice, the paradoxical but correct inference to draw is that a successful post-COVID teaching intervention does not subtract from what students have to learn but rather *adds* to it.

Our rationale for adding to the students' learning burden is best seen by carefully identifying the aims and general features of the proposed teaching intervention and assessment.

Intervention desiderata

The best way forward, in our opinion, is to *explicitly teach students the skills they need for **learning to learn***. Students will be deluged with facts when they return to school; we must equip them with skills to help them deal with the looming factual flood. Learning how to learn will enable students to better handle the accelerated pace of learning demanded. Such skills also improve student psychological well-being: when a situation is known to be manageable, stress levels go down.

COVID-19 has made it imperative that students learn faster; that they retain what they have learnt; that they make good life choices, especially concerning their studies; and that they develop both logical rigour and flexibility of mind so as to connect up questions and topics to which they have been exposed only briefly. Three baskets of skills appear to be especially useful in our present circumstances:

1. **Memory techniques.** Effective methods for developing a disciplined memory have been known since the Middle Ages. (Yates, 2001; Carruthers, 2008) With practice, it is possible to retain a remarkable number of facts.

2. **Decision making skills.** Making better decisions is a teachable skill. Goal-setting, prioritisation, and techniques such as SWOT analysis, PMI, and cost/benefit analysis are all useful and highly teachable. Students in the post-pandemic world will need to be efficient at organising their efforts.

3. **Applied logic skills.** In its applied form, logic is nothing other than the grammar of reliable thought. Logical thinking helps students discern connections among facts and empowers them to extrapolate new results. It is a reality in India that our students will face questions on high-stakes exams that they have never seen before or, at most, touched on but cursorily.

In light of the above, we strongly recommend a teaching recommendation that is based on SQ as this would include the three sets of learning skills described. There are rigorously-tested programmes already available on the market. (Singapore Ministry of Education, 2010) Since skills are acquired only through practice, and practice presupposes structured experiences, we suggest that programmes that teach via board games would be good intervention candidates. For more detailed recommendations, please contact either of the corresponding authors.

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