The Trillium COVID-19 Risk Assessment Index – Methodological Notes

Talissa Watson and Brendan Sweeney
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The Trillium Network for Advanced Manufacturing COVID-19 Risk Assessment Index is a multivariable tool that quantifies and compares the risk related to COVID-19 in 53 sub-sectors of Ontario manufacturing. This tool was informed by four key variables that aimed to quantify each sub-sector's risk of transmission and functionality amid the reopening of the economy due to its pre-COVID-19 business operational structures.

The first variable captures capital intensity. It does this by dividing each sub-sector's GDP by the number of employees within the industry for each year between 2001 and 2019, and subsequently taking the average over this time.[1] This measurement helps control for the level of automation in each sub-sector. Higher levels of capital intensity result in a lower risk score and lower levels result in a higher risk score.

$$Capital\ Intensity\ Proxy\ (CIP)\ =\ AVG\left(\frac{gdp_{ik}}{employees_{ik}}\right)$$
$$where\ i\ =\ sub-sector\ \&\ where\ k = year$$

The second variable captures the ability of employees to work remotely based on their occupational group within manufacturing. This measure uses the US Time Use Survey to determine the proportion of employees within different occupational groups that can perform some or all of their work remotely.[2] We then use Canadian Census of Population data to calculate the occupational mix (using NOC codes) across different manufacturing sub-sectors.[3] To ensure compatibility between the Canadian and US dataset, we converted the NOC codes to be consistent for the US occupational categories.[4]

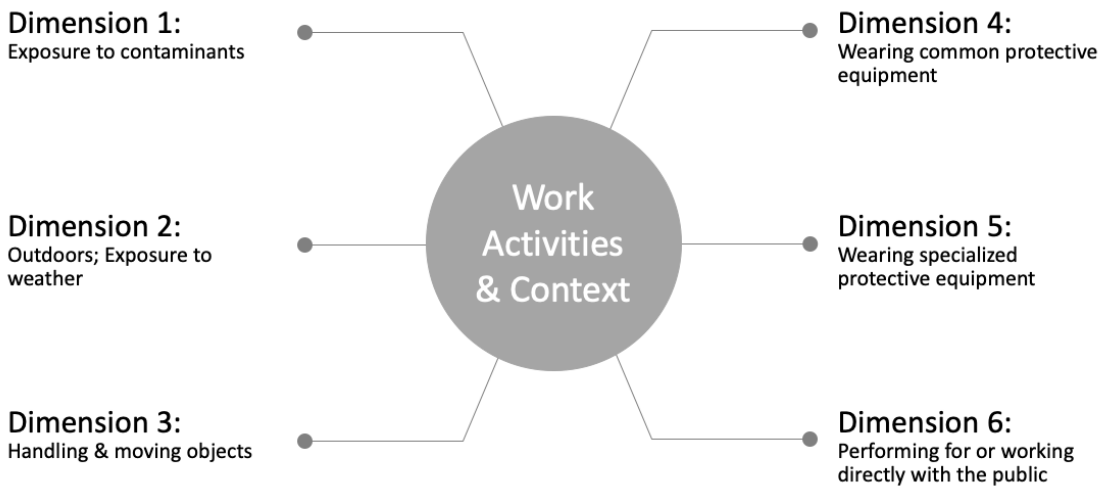
$$Ability\ to\ Work\ Remotely\ (AWR) = \sum \Pr\left(AWR_{ij}\right)$$
$$where\ i\ =\ sub-sector\ \&\ where\ j = occupation$$

The third variable captures employee behaviour. We used the US Time Use Survey to determine the percentage of employees in each occupational group that did work remotely, given they had the ability to do so. Canadian Census of Population data was used to identify the occupational breakdowns within sub-sectors of manufacturing. The greater the proportion of employees in any given sector who can and do work remotely, the lower the risk score (and vice-versa).

$$Employee\ Behaviour\ (EB)\ = \sum Pr(EB_{ij})$$
$$where\ i\ =\ sub-sector\ \&\ where\ j = occupation$$

The fourth variable captures additional work activities and context. This variable is based on dimensions set out in the Occupational Information Network (O*NET). These dimensions include 1) exposure to contaminants 2) exposure to the outdoors or weather, 3) handling and moving materials, 4) working directly with others, 5) wearing common protective equipment, and 6) wearing specialized protective equipment.[5] These dimensions were chosen based on our informed hypothesis testing and then validated by exploratory factor analysis, where those with a factor loading greater than a predetermined threshold were kept within the final computed score. A factor analysis was then used to combine these dimensions and compute an average score for each occupational group, such that the higher the score, the higher the risk. The factor analysis techniques created weights of importance for each variable within the model and the research can infer from fit indices in the model output that a one-factor model had the optimal model fit. These scores were normalized between 0 to 100 to simplify interpretability. An expected score was derived by using the proportional distributions of workers within each occupation in each segment and the computed risk score for each occupational category.

$$\textbf{Step One}: Work\ Activities\ \&\ Context\ =\ AVG(WAC(6\ dimensions))_{ij}$$
$$where\ i\ =\ sub-sector\ \&\ where\ j = occupation$$



$$\textbf{Step Two}: Ex(WAC_i)\ =\ \sum AVG(WAC_{ij} * Pr(Occupational\ Category))_{ij}$$
$$where\ i\ =\ sub-sector\ \&\ where\ j = occupation$$

We then formulated a score for each sub-sector that incorporated these four key variables. The factor analysis technique was used to attach weights to each variable depending on its importance to the final risk score. While the work activities and context variable communicated a high-risk rating when the variable itself was higher, this was not the case for capital intensity proxy, ability to work remotely, and employee behaviour, which equated to a higher risk when the variable was lower. This led to an overall risk score that communicated greater risk when the value was lowest. In order to simplify the index, we took the inverse of the computed scores and normalized the scores between 0 to 100. In doing so the closer the computed score was to 100, the greater the overall risk for that manufacturing segment.

$$Risk\ Assessment\ Index\ (RAI) = (RAI(4\ dimensions))_i$$
$$where\ i\ =\ sub-sector$$

Green, Siu, and their colleagues also used the (O*NET) to quantify occupational attributes within their VSE COVID-19 Tool.[6] While informed by their methods, the Trillium Network for Advanced Manufacturing COVID-19 Risk Assessment Index differs from their tool in that it focuses on manufacturing sub-sectors and takes an aggregate view of employees within each segment. The capital intensity variability serves as an additional proxy for the level of automation and physical proximity and the work activities and context variable captures additional worker attributes that may impact the chances of viral transmission. We also attempted to account for manufacturing industry specific occupational characteristics, such as handling and moving objects, which may take place on production lines. We then focussed on differentiating between the ability and behavioural patterns of employees in relation to working remotely. We did so to account for the workplace conditions that will potentially persist as we readapt to these new circumstances and emphasize the behaviours that will return overtime as Canada proceeds with its reopening strategy and worker confidence improves. The US Time Use survey proved particularly useful in providing this information. We hope this methodological approach will advance the conversation in determining policies and strategies that promote the safety and health of employees within Ontario manufacturing.

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