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Transportation, the pathogen vector to rule them all: Evidence from the recent coronavirus pandemic

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ABSTRACT

Introduction: It is common knowledge that mobility refers to a distinct vector for pathogens, but the importance of prevention and the infusion of public health practices within transportation systems is not manifest. Replication studies of this effect are important because transportation remains veiled in modern societies, since its demand is not direct, but derived.

Methods: Variables mirroring transportation and logistics’ systems intensity (trade data, the logistics performance index, and investment in transportation) are cross-tabulated with epidemiological data from the recent coronavirus pandemic. As the samples of the data pertain to a dependent commonality, the statistical hypothesis test applicable is McNemar’s test. In addition, the statistical power of the test(s) is calculated as a marker of methodological validity and reliability. To further strengthen the analytical methodology, a plethora of descriptive statistics have been calculated and multiple correspondence analysis (MCA) has been conducted.

Results: This work confirms that the domain of transportation bears a strong association with not only mortality of a disease, but its recovery rates as well. All crosstabs provide statistically significant results and the statistical power calculated is very high, signifying the appropriateness of the methodology and the very low probability of Type II error. The MCA results are significant, as well.

Conclusions: The impact, or even the presence of transportation is veiled, as transportation comprises of derived demand dynamics. As such, its activities and even the prerequisites for its efficient operations many times go unnoticed. This work replicates a known effect, that mobility exacerbates the presence of a pathogen. The significance of this research lies on the fact that distinct indicators that reflect transportation and logistics are (though a robust calculatory methodology) statistically associated with epidemiological data.

1. Introduction

The importance of transportation is paramount and cannot be overstressed, as almost everything requires mobility to function. Yet, this very important function remains, from the dawn of human history, the salient vector for disease, as responsible for the “microbial
unification of ... the world” (Le Roy Ladurie, 1981). Transportation and its correlation with disease is firmly embedded in society, and not only in the domain of the health sciences. A plethora of instances could be employed to portray this association. One indicative example is rooted in the works of Nikos Kavvadias, a celebrated Greek poet, whose poetry, with influences from Baudelaire (Menelaou, 2017), was for many decades recited in merchant vessels across the globe by seafaring personnel from a wide variety of backgrounds and cultures. The rendition of blended quasi-realism and non-fictional accounts from his travels render him a prime symbolist of nostalgia. His talent in presenting the unrefined dynamics and paradoxes of human beings, whether in referencing drug use, societal disruption, or prostitution, within an amalgam of a narrative exotic, is unique. His accounts are there to satiate any person’s psyche with romanticism, childhood innocence, shattered dreams, and raw truth, all with shocking details. In his novel ‘The Shift,’ which was published in 1954 and celebrates a sailor’s life rather romantically and through conflict, with “a prose on the life of the sailors blending poetry with personal memories that reveals ... unique narrative talent ...” (Paganopoulos, 2007), one can discover a plethora of shipping culture threads, many of which are apparent even today (Stavroulakis et al., 2019).

In the second chapter of the novel one reads: The Captain asked, “are you afraid?” and the sailor answered, “I do not care even if I drown, the only thing I’m afraid of is disease.” He then paused, only to add to his last remark, “... and women.” The Captain replied, “well, all of us are afraid of women, especially the ones in ports.” The sailor said, “no ... I am not afraid of the women in ports ... I’m afraid of the other women, the upstanding ones, the ones that are educated, the ones that we marry.” In the sixth chapter one reads: “... he lay there full of blemishes – could it be the heat, or the fever? ... he reminisces: her eyes were kind, and I’m sure that if she were sick, she would have told me.” Later on in the text one reads, “TTT (Morse code of the ‘Sécurité’ maritime signal) ... medical advice ... sailor of twenty-five ... fever forty-one ... probably of contagious water ...” (Kavvadias, 2015).

Before a raised eyebrow reflects the notion of why a paper on transportation and health mentions prostitution in its introduction, a binding and uniform desire is manifested; one would only wish that Kavvadias’ accounts pertain exclusively to the fictional. They do not. AIDS was first documented clinically in 1981. However, the first (documented) case of HIV marking the presence (and introduction?) of the virus in Europe was through a Norwegian sailor that started exhibiting symptoms of the disease in 1967. The sailor had visited African ports several times before 1966 and was known to have contracted sexually transmitted diseases “at least twice” (the case referenced has been extracted from Freland et al., 1988, quoted phrase included). Furthermore, in 1967 the Norwegian sailor’s wife started developing symptoms of AIDS and the same year their daughter was born, who started developing symptoms two years later, in 1969. All three, the sailor, his wife, and their daughter, died in 1976. Autopsy results confirmed the presence of (a rare type of) HIV (Jonassen et al., 1997). Europe’s patient zero with reference to the HIV epidemic was destined to materialize in the tragic case of this family’s decimation. One may conclude that Kavvadias’ accounts above, though rather crude (and discriminative), may be considered to belong to the domain of the borderline romantic and innocent, when contrasted with factual circumstances.

Alas, shipping is not the only mode to be blamed, as it concerns only one form of conveyance; one could even consider shipping not to be that responsible for pandemics today, as (e.g.) aviation might pertain to a more effective vector for airborne pathogens (Tiwari et al., 2021). Or better yet, that the problem does not stem from the trade of goods or freight in general, but solely from passenger transportation. As much as this notion may be alluring to explore, the issue is not endemic neither of a specific mode, nor of a type of cargo or conveyance medium, but of transportation in general; though interestingly enough, and since the first reference presented herein belongs to the domain of shipping, maybe it would be appropriate to reflect that even the term ‘quarantine’ is shipping-derived (from the forty-day isolation during which ships had to remain at port throughout the ‘Black Death’ pandemic, cf. Etymologica: Quarantine, 2013).

The index case (patient zero) of HIV in the US was (for many years deemed to be) a Canadian flight attendant (McNeil, 2016). He was depicted as a villain at the time but later exonerated, as on the one hand, he was just one of many (simultaneous) cases, and on the other, the virus had entered the States from the Caribbean (Nature Editorial, 2016; Worobey et al., 2008). Analysis of the Canadian flight attendant’s direct and/or indirect sexual partners revealed many outbreaks in US cities, correlated among the latter. Maybe this is the parameter that engulfed many in the need to portray this person as the scapegoat. Regardless, again, the common thread between the poetic accounts above and the introduction of HIV in the United States is one, and it is transportation. It could be traced historically that the same stands for plague (fleas and rodents in vehicles/vessels as the vector), cholera (water in vehicles/vessels as the vector) – could this be the manifestation of the case of infected water mentioned by Kavvadias? –, and influenza, to arrive at the severe acute respiratory syndrome (SARS); all borne through transportation. The latter is a coronavirus representing one of several global pandemics originating from Southern China (the references to the vectors for plague, cholera, influenza, and SARS are all extracted from Tatem et al., 2006a).

Transportation many times tends to denote passive and implicit importance and one reason for this may be the fact that, for the most part (cf. Mohktarian and Salomon, 2001), it attests to a derived demand, in the manner that there is no actual demand for a vessel’s movement per se, but only for the commodities within its holds. Accordingly, the importance of transportation as a governing vector of disease remains obscure, and so do preventive tactics for the mitigation of pandemics through transportation systems. Whether the vector is a rodent (plague), mosquitos (able to reproduce in water canisters in ships and carrying yellow and dengue fever, among others), or human beings (the real Black Death vector), in all circumstances the binding agent is mobility (cf. Tatem et al., 2006a). The very source of life and its quality pertains to a derived vector for disease.

For centuries it has been a given that transportation stands to proliferate the impact of pathogens and contaminants (Tainio 2015; Tatem et al., 2006b), as it undoes isolation. Yet, said correlation has not been studied extensively, and even more so, preventative measures and the introduction of public health mandates across transportation are only visible when contagion is in progress, as in the recent coronavirus pandemic. The present work provides strong empirical evidence of the correlation of transportation activity, such as the (prerequisite, implied, and) derived activity of trade, logistics performance, and investment (in transportation) with the epidemiological variables of mortality (indicated through case fatality) and recovery, utilizing data from the latest coronavirus...
pandemic. These results are important, owing to the replication and validation of the association between transportation and disease. Furthermore, results such as these can proclaim the dire need for resilient and sustainable transportation and logistics systems rooted in preventive dynamics and public health determinants (Cohen et al., 2014; Marshall et al., 2014).

Global trade and transportation have witnessed great strides in efficiency, security, supply chain visibility, standardisation, technology, and innovation. Still, as manifested from the latest pandemic, common-sensical pillars of transportation safety and resilience are absent, and in their nonattendance, mobility has been transformed from a catalyst of life to a practical instance of chaos theory, where a pneumonia cluster linked to a wholesale market can lead the global economy to a halt (not to mention the loss of human lives). Research results, such as the ones that are relinquished herein, can provide the direction for more robust systems of mobility, through effective strategy and policy initiatives (cf. Gunn et al., 2020). The paper is organized as follows; after the present section, a literature review is conducted validating the objectives and rationale of the research. The review is followed by an analysis of the methodology executed, which is succeeded by the results’ section. The paper concludes with a discussion that touches upon the relevance and impact of this replication study and its spillovers to policy and further research.

2. Literature review

In 2003, the SARS outbreak began because of a single case in China, and studies correlated that outbreak with the existence of the (then) ‘novel coronavirus’ (Drosten et al., 2003; Ksiazek et al., 2003; Peiris et al., 2003). In 2019, a market in Wuhan was the epicentre of the most recent outbreak (Zhu et al., 2020), of the now (novel) novel coronavirus (Chen et al., 2020). This outbreak has impacted many important functions of nearly all countries of the globe (Zhang et al., 2020) and is responsible for severe loss of life (over three million people at the time of writing the present paper). Economies have come to a standstill, and nearly all aspects of society that can bear an electronic counterpart have shifted towards new paradigms of virtual manifestation and execution. Most countries have faced recurring lockdowns, quarantines, and extreme pressure on public health infrastructure, as the systems in place are strained to their limits, in a situation without precedent (Gargoum and Gargoum, 2021). In addition, the measures taken with reference to isolation, i.e., any quarantine – related decisions, may within themselves be erroneous, as these measures have been found to work when shipping has been the latent vector, precisely because mosquitoes, rats, and fleas, can actually be contained within a vessel (cf. Horden and Kinoshita, 2014, Chapter 16 by R. Sallares). Thus, lockdowns and quarantines are effective when the vector can be contained within a system with clear and isolated boundaries (such as a ship). In circumstances where the systemic boundaries are permeable (such as a nation, or a geographical location), it is logical to be assumed that a quarantine will not work, as it does not really isolate the vector.

Business in nearly all sectors has completely shifted its day-to-day operations and telework is becoming the new norm (Belzunegui-Eraso et al., 2020; Carillo et al., 2020; Chong et al., 2020; Jesus et al., 2020; Lebopo et al., 2020), compelling new controversies in the work-employee system to be born (Lengen et al., 2020). Many educational institutions have welcomed their first-year students via a teleconference platform this academic year, with hopes that faculty and students will soon be able to meet in person, like the (not so) old days. Following the bulk of education taking place online, once again one can witness novel issues that include not only ‘innovations’ in cheating (Bilen and Matros, 2021), but opportunities as well, such as the reduction of the educational sector’s carbon footprint (Filimonau et al., 2021). Preventive and/or mitigative measures for the pandemic tend to affect not only economies, but also the wellbeing of all strata of society (Bonati et al., 2021; Cenat et al., 2021; Chakraborty et al., 2020; Chaturvedi et al., 2021; De Man et al., 2021; Fu et al., 2021), with effects in the long term that are yet to be exhibited, but that surely reside outside the scope of forecasting (some certainty) and scenario planning (less certainty) and are probably situated in the realm of speculation (uncertainty).

Apart from the loss of life, shocks in infrastructure, disruption in supply chains, and wounds in economies, the residual effects in humanity may be too extreme to ponder, and this may be valid for instances encompassed in either end of the qualitative spectrum (enduring dysfunctional externalities vs. opportunities for sustainability). Particularly distinct is the effect of the pandemic on mental health (Dam et al., 2020; Fang et al., 2021; Su et al., 2021), as mitigation measures such as (physical and resulting mental) social distancing, lockdowns, and quarantines (among other factors) have stressed many individuals’ psyches to retrenchment. Many negative implications with reference to mental health have been documented (Almeda et al., 2021; Fukase et al., 2021; Lee et al., 2021; Li et al., 2021b) and an accentuation has been observed with respect to insomnia and psychological reactions, especially when a pre-existing condition has been present (Sun et al., 2021). Maybe this pandemic has just begun taking its long hold onto the world, with side effects that will persevere for decades. Or maybe, this regrettable context will pose the baseline for a new paradigm in societal systems; one based on the endurance of human values.

The recent pandemic has provided the seed to produce a plethora of research for multiple domains (Lemke et al., 2020; Li et al., 2020; Musselwhite et al., 2020; Wang et al., 2020a), not (necessarily) confined in the realm of medicine (Samal and Jena 2020). A substantial aspect of this research is focused on the mobility mechanisms of the disease, inclusive of transportation (Demek et al., 2021; Noland, 2021; Rubenstein et al., 2021; Li et al., 2021a; Nikolaou and Dimitriou 2020). While editing the present revision of this section, a Scopus™ search with the keyword ‘COVID-19’ returns over 132,000 document results, with over 84,000 of these published in 2020. Google Scholar™ returns about 144,000 results for the same query and the temporal range of 2019 onwards. Just for a comparison, and not that the two can be compared as such, but only to give a reference point, a Scopus™ search of the term ‘Facebook’ returns just a bit over 29,000 document results. As mentioned, the aspect of transportation has indeed attracted a segment of the current COVID-19 related research, again inclusive of many factors, such as (indicatively) the dynamics of dispersion (Ivanov, 2020), resilience (Ivanov and Dolgui, 2020), global consciousness (Galvani et al., 2020), and public satisfaction (Dong et al., 2021).

At the same time, this pandemic provides the opportunity for the institution of new policies (Gray, 2020), technologies (Kazemzadeh and Koglin, 2021; Zeng et al., 2020), and planning towards a resilient (Hobbs, 2020), sustainable (Gössling, 2020; Jiang et al., 2021), more humane, and public-health-rooted infrastructure for transportation, and ergo, society (Lucchese and Planta, 2020). Still,
there are enduring gaps in the knowledge and understanding of the fundamental mechanisms of transmission (Fu and Meng, 2020; Huang et al., 2020). Notwithstanding, there seems to be present creative problem solving, ranging from innovation (Chesbrough, 2020) to immunity analysis (Eichenberger et al., 2020).

The coronavirus outbreak has severely altered, besides distinct operational sectors (McEwan et al., 2020), not only the global economy (Gern and Hauber, 2020; He et al., 2020; Zhang et al., 2020), but also food security (Deaton and Deaton, 2020), intercultural relations (Schwartz, 2020), production (Olivo, 2020), sports (Parnell et al., 2020), tourism (Jamal and Budke, 2020; Setthachotsombut and Sua-iam, 2020; Yang et al., 2020; Ying et al., 2020), and supply chains (Lemke et al., 2020; Singh et al., 2020). New technologies are employed for mapping (Kamel Boulos and Geraghty, 2020) and many outlets are recording lower levels of pollution, although many pollution events have not been avoided during the outbreak (Wang et al., 2020b). As expected, the dent in supply chains is more than disruptive (Ivanov 2020) and the resilience of transportation systems is put to the test (Ivanov and Dolgui, 2020). There are also voices echoing the concern that this situation is rather an aftereffect of rudimentary societal failure, more than anything else (Prashad, 2020).

Research has been dedicated to documenting the dynamics of the pandemic (Holshue et al.; Wu et al., 2020), extracting factors that can be correlated with the mortality of the disease (Guan et al., 2020), such as air pollution (Filippini et al., 2021; Suthar et al., 2021), ethnicity, education, and income (Figueroa et al., 2021). The infrastructure of transportation, commerce, and public health has been included in these factors (Romero et al. 2021; Li et al., 2021). As mentioned, transportation is to be considered a prime vector for viruses (Grais et al., 2003), providing a plethora of research opportunities for modelling (Rvachev and Longini Jr. 1985; Brockmann and Helbing, 2013; Colizza et al., 2007), as well as the mitigation of risks (Tatem et al., 2006). Despite the fact that various solutions have been provided, even within transportation geography and for more than a decade (Luke and Rodrigue, 2008), the coronavirus found the whole world (once again) unprepared. Disease proliferation is known to be exacerbated by transportation, through all modes; from walking to aviation, and from passenger transportation to the mobility of freight (Chung, 2015). The correlation of transportation and disease has instigated research in the past (Park et al., 2017), as spatial dynamics invariably involve vectors for disease (Wilens, 2007). Many mitigating solutions have been proposed (Gold et al., 2019), as the function of mobility (and not necessarily only of humans, cf. Hsu et al., 2012) remains the main vector. Of course, the matter is not solely contained in the transportation sector but percolates to others, one prime example concerning policy (Seelke et al., 2016). However, sustainability remains the bone of contention (Oke et al., 2019), that can be attained through a plethora of solutions, including trust (Alonso Tabares, 2021), the optimum utilization of technology (Feroz et al., 2021; Mohammed and Isa, 2021), and the redefinition of societal systems, interpolating energy (Mohideen et al., 2021) and logistics (Nandi et al., 2021).

One would be remiss amid a pandemic not to refer to one of the fathers of epidemiology, John Snow. If only the world could have his insight during these times; although his legacy is alive and well, in the one true post hoc saviour within the chaos of the pandemic, the functioning infrastructure of public health. Only if societies invest in the a priori value of the collective deployment of a culture of effective public health systems, the world can bathe in the bounty of the full spectrum of public health benefits; mitigatory and preventive. Regrettably, the primary societal focus on accounting cost and subsequent myopia with reference to ensuing societal, environmental, and health costs, has granted resilience not to prevention, but to destruction. Snow’s contribution began with research of clusters, and maybe these constructs will pertain to solutions in the present situation. It could be observed that the importance of the cluster concept (Kolousis et al., 2017, 2018a, 2018b), especially for the pandemic (Chan et al., 2020; Desjardins et al., 2020), is as prevalent as it was in the days of the miasmic decree, when Snow laid the cornerstone of public health. A note should be inserted here, that cluster theory may pertain to viable solutions, in the same manner that Snow’s cholera clusters gave birth to epidemiology, on the grounds that what sets clusters apart is the stance with respect to a culture of health and mutualism (Stavroulakis and Papadimitriou, 2016, 2017). Not only this, but current research has already relinquished instruments for the study and assessment of a variety of variables in clusters, including geographical and transportation systems’ aspects, as well as elements of a culture of prevention, health, and sustainability (Stavroulakis et al., 2019, 2020, 2021).

Within the present systemic framework, it would be interesting to investigate the association of transportation with epidemiological data from the pandemic. Transportation involves derived demand. The quote many times in the industry involves the statement that nobody ever woke up feeling the need to move a container across the world. The need, and, thus, the demand, is for the commodities in the container; not for the mobility of the container itself. As such, transportation intensity can be modelled using many variables that mirror the volatility of mobility, without necessarily referring directly to transportation. On the other hand, the methodology of crosstabulation is used extensively in the literature, to examine the association of a factor to an effect in a variety of disciplines (Adeniyi et al., 2020; Davidson et al., 2021; Kim, 2020; Lautamatti et al., 2020; Mbanze et al., 2020; Wall et al., 2021). As such, the hypothesis may be formulated that crosstabs could be utilized to investigate the association of transportation variables with epidemiological data. It is extremely helpful when the variables under examination are categorical and dichotomic, but even if this is not the case, through variables’ transformation it is possible to proceed with the use of crosstabs, as will be demonstrated herein. The section analysing the methodology employed is as follows.

3. Methodology

3.1. Variables

The methodology utilized pertains to an established process for epidemiology, with relevant applications for other sectors (Datta et al., 2020; Marchesan et al., 2020; Messi et al., 2020), including transportation (Kolousis et al., 2019). Two categorical variables are investigated as per their association, through simple two-by-two contingency tables. These variables refer to two categories. The first one encompasses transportation-related data and comprises the markers of trade (imports and exports as a percentage of the gross
domestic product for each country), logistics performance, and transportation investment with private participation. Longitudinal ‘World Bank Open Data’ has provided the raw data with respect to the dichotomous variables mirroring transportation (the factor category; the exact definitions and methodology for extraction and calculation of these variables are included in Appendix A). Apart from the variables of trade (imports and exports) that suggest intensity of transportation, an indicative marker that also reflects transportation and is included in the present work pertains to the ‘Logistics performance index: Quality of trade and transport-related infrastructure’ (LPI). Following a Likert-type ordinal scale (Albaum, 1997; Allen and Seaman, 2007; Likert, 1932), this indicator can categorize the quality of transportation and logistics infrastructure. The LPI is an aggregate of a comparison of measurements, including logistics services (encompassing customs and border control, among others), transportation infrastructure quality, traceability of logistics networks, timeliness, and quality of logistics services (The World Bank, 2018). The final ‘transportation marker’ selected pertains to ‘Investment in transport with private participation,’ as another variable of transportation systems’ extrovert and intricate nature (The World Bank, 2020). This indicator will go ahead and provide a sign as to the culture and policy of a nation, since the amount of investment in transportation portrays prioritization of national policy. In comparison with the rest of the variables, different aspects as to the culture, intensity, outlook, and sustainability of transportation can be obtained. The specific variables selected herein have been extracted as indicative of the transportation footprint of a nation, as well as its infrastructure and intensity; future research can scrutinize the correlation of other pertinent transportation indicators with pandemic metrics. As included in Table 1, the specific indicators can reflect different aspects of transportation, including the quality of its infrastructure, its intensity, and the national dedication in transportation planning and outlook. Even though the variables opted in the present paper refer to distinct elements and parameters that can mirror transportation intensity, for the purpose of being laconic, henceforth, they will be descriptively referred to as ‘transportation’ variables (even without emphasis).

The second group of categorical variables refers to recovery and mortality rates (the condition) of the novel coronavirus pandemic, as retrieved from Worldometer™ data (the dataset of this study includes data from the first outbreak until the end of January 2021). Recovery and mortality rates are prime epidemiological indicators. The mortality rate concerns the deaths in a specific population (for this work the specific population refers to countries) from a specific cause. It is defined as “the number of deaths occurring among the population of a given geographical area during a given year, per (e.g.) 1000 mid-year total population of the given geographical area during the same year” (Handbook of Vital Statistics Systems and Methods, 1991). In this context, mortality has been expressed as the ratio of COVID-19-related deaths in a given country to the COVID-19 cases in the same country (which results in the case fatality ratio, cf. Bonita et al., 2006). Consequently, case fatality is utilized as the mortality indicator herein. The recovery rate is defined as “the rate of transition from the state of the infected with the disease to the recovered from disease” (Greenhalgh and Day, 2017). As with the mortality rate, the recovery rate is calculated as the ratio of recovered individuals to the total number of COVID-19 cases in a specific country.

### 3.2. Multi-correspondence analysis

Association among transportation intensity variables and COVID-19 data was also examined with multiple correspondence analysis (MCA). MCA is an exploratory multivariate data analysis method, which allows the simultaneous examination of multiple categorical variables and produces a map of the derived relationships, and as such it is applicable to the present dataset. Furthermore, this analytical instrument has been used extensively in health and transportation research (Baireddy et al., 2018; Cavaignac and Petiot, 2017; Collazo, 2019; Das et al., 2020; Dias et al., 2019; Fan et al., 2020; Hamon 2020; Jalayer et al., 2018; Jimenez-Delgado et al., 2019; Leonardi et al., 2019; Millogo et al., 2021; Natarajan et al., 2020; Simoes et al., 2020). MCA provides a joint representation of row and column categories in the same dimensionality, which enables the identification of groups in proximity (Hair et al., 2013). Multiple correspondence analysis is able to convey frequency tables into a graphical representation of the data; the graph of points with its dimensions helps to identify the main characteristics of the examined data (Bartholomew et al., 2008). This analytical methodology provides the possibility of simultaneous examination of multiple variables for effective mapping of correlations; thus, it can be of service to the present study.

As will be demonstrated with the results of the Kolmogorov-Smirnov and Shapiro-Wilk tests, along with the visual observation of the histograms (that are all non-symmetrical, as included in Appendix B), and descriptive statistics calculated (where, apart from the fact that all means diverge from medians, skewness and kurtosis values are representative), it could be deduced that all the variables

### Table 1

| Indicator | Transportation effect |
|-----------|-----------------------|
| Imports   | • Transportation intensity (Rodrigue, 2012) |
|           | • Liberal or protectionist policies (Carballo et al., 2017) |
| Exports   | • Expansion or contraction of the economic cycle (Carballo et al., 2017) |
| Logistics performance index | • Quality of transportation and logistics infrastructure (Arvis et al., 2018; The World Bank, 2018) |
|           | • Scope and effectiveness of logistics (Beyesenbaev and Dus, 2020) |
|           | • Integration level for logistics (Rainbekov et al., 2017) |
| Investment in transport with private participation | • Dedication to planning of transportation infrastructure (Batool and Goldmann, 2020) |
|           | • Prioritization of policy and governance (Percoco, 2014) |

* Not an exhaustive list of effects.
included herein do not follow the normal distribution, as none comply with the standard normality tests (Field, 2013). Notwithstanding, correspondence analysis refers to a non-parametric method and, consequently, there is no requirement with reference to normally distributed data (Siomkos and Vasilikopoulou, 2005).

3.3. Crosstabulation

The inclusion of both epidemiological rates assists the analysis towards a more inclusive approach, due to the fact that the research is garnished with not only a negatively connoted rate, but also with its opposite, hence granting diversification in the analysis. In addition, dependence of one rate - but not of the other - could signify specific circumstances where further research and policy directions could be pursued. The four transportation variables are cross-tabulated with the two epidemiological variables, thus producing eight crosstabs (Appendix C). The research question is then formulated as ‘does the variable of transportation, as exhibited through the specific indicators, bear any association to recovery and mortality rates of the novel coronavirus pandemic?’

The research question is addressed with the use of the formulated contingency tables (Fig. 1), each time examining the association of (either) imports or exports, logistics performance, and investment in transportation, to (either) mortality or recovery, ergo, relinquishing the (eight) distinct contingency tables (Appendix C). The specific variables have been selected to portray transportation intensity, as they are included in several different aspects of the manifestation of mobility for a country. Especially with reference to the number of imports and exports, they can illustrate the policy of a region and its inclusion in either a liberal or a more protectionist approach in international trade. These markers have been indicative of the expansion of the economic cycle and the need for transnational collaboration (and trade, cf. Smith, 2007), along with international transportation infrastructure and technology that can sustain this type of growth.

One prerequisite for the extraction of crosstabs is the inclusion of the variables in a dichotomous context. As the plethora of the indicators included herein (apart from the Likert - type LPI variable) refer to continuous numerical data, the first hurdle (and origin of modelling allowances contributing to the limitations of this study) to be bypassed for the extraction of the crosstabs refers to the transformation of the continuous variables into dichotomous categorical variables (as necessary to generate the contingency tables). This process has been conducted through the introduction of a cut-off point to designate the inclusion of a specific case in one of the two dichotomous groups. The selection of this threshold is fundamental, as it will set the baseline for the ensuing calculatory methodology. Based on the body of research, one could select the average (Balmford et al., 2019; Becker et al., 1998; Cohen, 1983; Creel and Loomis, 1997; Dougados et al., 2012) and/or the median (Kim, 2018; Teshima et al., 2019). The decision of the threshold is, of course, not to be left to chance. One might think that the selection of the threshold should follow the statistical hypothesis methodology for samples’ comparison. Should the underlying distribution be normal, then the average and the median refer to the same metric, and, therefore, either indicator can be selected. In the same manner, unless the average diverges substantially from the median, it can be utilized without the introduction of significant bias in the analysis. Thus, one might ponder that for the present dataset, any categorical variable included in a specific crosstab must follow a normal distribution for the average to be utilized as a cut-off point, and if not, that the median should be used as the threshold, but this is not the case.

The issue with the approach of median selection as a measure of central tendency is that it works for samples’ comparison, because normalization (or equalization) is the key, but the same does not apply for a crosstab calculation. The selection of the median shall introduce bias in the calculation, as the threshold will equalize the data, when the goal is to document the skewness of the joined categorical variables. If the median is selected, then the crosstabs will not produce valid and reliable results, due to the ‘biased’ nature of the cut-off point in normalizing the data. For this reason, the average should be selected as the threshold dividing the variable into two distinct groups. Through this methodology, the continuous variables are transformed into dichotomous categorical data, and the statistical decision test based upon the dependent nature of the data can portray any instance of association of the two variables in an effective manner. Dichotomization is an appreciated practice when there is skewness present in the data (MacCallum et al., 2002; Livas and Scotis, 2021), as in the current study, which, as mentioned, pertains to data that is not normally distributed. It might be interesting to note that the World Bank database utilized, many times inserts a separate marker for comparison, which refers to the ‘World

Fig. 1. The contingency table (source: Authors, MS Visio™ output).
Average’ (The World Bank, 2021).

It could be argued that if there are cases in either end of the threshold (and independent of threshold selection, as the argument pertains to the average or the median), and very close to it, then these cases are to be included in a specific group and rendered as equal with values residing at either extreme of the datasets. This instance, of course, pertains to a modelling allowance that one must abide, but notwithstanding, the risk of Type II error may be calculated post hoc. Thus, one can extract an indicator of the discrete probability of accepting a false null hypothesis. Through the calculation of the power of the test, and provided this is high enough, one holds an indication of the methodological validity and reliability of the results. If there is a low probability of Type II error and, thus, a high value for the power of the test, it could be concluded that the methodology will not introduce substantial bias in the results. Thereby, the present analysis concerns two statistical classes, where the threshold of each class is the average of the dataset. Therefore, (e.g.) countries with import/export data of less than the world average are included in the low transportation intensity class (group annotated as ‘LOW’ in the crosstabs), while countries with imports/exports more than the world average are included in the high intensity class (group annotated as ‘HIGH’ in the crosstabs); the same is executed for all transportation variables. Similarly, countries with higher recovery/mortality rates than the world average are included in the high intensity class, whereas countries with lower recovery/mortality rates than the world average are included in the low intensity class. The steps towards the formulation of the model and the different crosstabs extracted are depicted in Fig. 2.

The sample of the study consists of the dataset available for both variables. This ranges from one hundred and fifty-three countries for trade data, to one hundred and forty-five and one hundred and forty-two (for mortality and recovery rates respectively) countries for logistics performance, and fifty-six for transportation investment. Each country’s count is included in one of the four categories of the respective contingency table.

3.4. McNemar’s test

The association of the variables is investigated through the McNemar (1947) test for dependent nominal data. In his paper, McNemar dictates the norms to be followed for the designation of dependent data. If there is any indication of an association between the samples (either through measuring the same subject of analysis in two temporal instances, or any kind of pairing or dependence in the samples), the latter are deemed dependent. Transportation pertains to a global indicator, as what happens in one region affects another. As such, transportation and logistics samples cannot be considered independent. The same stands for epidemiological data, as well. At the same time, the data is mutually exclusive, i.e., not paired, as one country can only be included in one of the four cases of the crosstab.

This statistical decision test examines marginal homogeneity (as per the equality of row and column marginal frequencies of the contingency table, as in Table 4). McNemar’s test (its generalized version) pertains to a test sample as \((x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\). The null hypothesis \(H_0\) is \(P(X < Y) = P(X > Y)\). Let \(n_1 = \# \{i: x_i < y_i, i = 1, \ldots, n\}\), \(n_2 = \# \{i: x_i > y_i, i = 1, \ldots, n\}\) and \(r = \min(n_1, n_2)\), wherein

![Fig. 2. Formulation of the model (source: Authors, MS Visio™ output).](image-url)
Tests of normality (source: Authors, IBM SPSS and n investgate any discrepancy from the expected ratio. The (two-tailed) calculated probability (p-value) is included in Equation (1).

\[
\text{Exact} \; p\text{-value} = 2 \times \sum_{i=0}^{\infty} \binom{n_1 + n_2}{n_1} (1/2)^{n_1 + n_2}
\]

(1)

For the two-by-two contingency table, the null hypothesis asserts that \( H_0: \pi_{12}/\pi_{21} = 1 \), whereas \( H_1: \pi_{12}/\pi_{21} \neq 1 \) (Table 4). For an accepted significance level (\( \alpha = 5\% \)), if the p-value < \( \alpha \), then one can ascertain statistical association. Therefore, were the null hypothesis of the statistical test to be rejected, this result would be important, as it pertains to the association of the variables, i.e., transportation intensity is indeed associated with the mortality and recovery rates of the COVID-19 pandemic. Furthermore, the power of the statistical decision test is computed to bear an indicator of validity and reliability. The power of the test (achieved power \( = 1 - \beta = 1 - \text{probability of Type II error} \) is an important validation of the methodological instruments selected.

4. Results

4.1. Tests of normality and descriptive statistics

The tests of normality produce the result that not one variable follows a normal distribution. Therefore, if one wishes to compare means, the median should be utilized as a measure of central tendency of the dataset. But for the compilation of the crosstabs, the indicator of the average is utilized to portray the skewness in the phenomenon appropriated in the contingency tables. The descriptive statistics are included in Appendix B, along with the histograms and boxplots of the variables. These indicators solidify the selection of the average, as divergence from a symmetrical distribution can be detected; an instance that can be captured effectively with the calculation of the average. In Appendix B, one can even observe the cases in the cruise ship MS Zaandam as a boxplot outlier of Fig. 7 (of course this data is not included in the crosstab as there is no respective transportation data for this object of study). Table 2 portrays the results of the variables’ normality tests. As can be noted, the variables do not follow a normal distribution (the Null hypothesis of normality for all tests is rejected). In addition, in all cases the mean diverges from the median (Appendix B). It is then concluded that the data is representative for the methodological formulation, as the selection of the average will be able to effectively document the disparities of the phenomenon, as well as any association between the variables included in the crosstabs.

4.2. Multi-correspondence analysis

As mentioned, correspondence analysis facilitates the visualization of relationships between the categorical data by providing a meticulous description of practically every bit of information embedded in the data (Greenacre and Hastie, 2006; Johnson and Wichern, 2007). Multi-correspondence analysis, as an extension of correspondence analysis (CA), allows to thoroughly examine the pattern of relationships of numerous categorical dependent variables (as is the case for the dataset of the present work). The graphical visualization of the results provides a structural organization of the variables and categories in a dimensional space (the dimensions or axes) on a joint plot diagram that is useful for identifying patterns in the data. The associations between the investigated parameters are also reported, where smaller distances between the data portray a higher degree of variables’ correlation (Greenacre and Hastie, 1987).

Therefore, a set of potential contributing factors which may influence the COVID-19 pandemic were indeed established using the MCA approach. To carry out the analysis, variables were divided into two groups; the variables of transportation (exports, imports, LPI, and investment) and the COVID-19 data (mortality and recovery rates), exactly as in the crosstab formulation. Prior to the analysis, all the continuous variables have been dichotomised by a median split, as appropriate to perform the MCA analysis. Although dichotomization may pertain to an extreme transformation for variables, it is an accepted method, where skewed data are present (MacCallum et al., 2002; Livas and Scotis, 2021), as is the case in this work. Through the MCA analysis, each principal inertia value is expressed as a percentage of the total inertia. These values measure the amount of variation accounted for by the corresponding principal dimension.

| Tests of Normality | Kolmogorov-Smirnov | Shapiro-Wilk |
|--------------------|--------------------|-------------|
|                    | Statistic | df | Sig. | Statistic | df | Sig. |
| Mortality          | 0.235     | 218 | 0.000 | 0.492 | 218 | 0.000 |
| Recovery           | 0.160     | 218 | 0.000 | 0.791 | 218 | 0.000 |
| Exports            | 0.164     | 239 | 0.000 | 0.749 | 239 | 0.000 |
| Imports            | 0.130     | 239 | 0.000 | 0.809 | 239 | 0.000 |
| Investments        | 0.319     | 81  | 0.000 | 0.552 | 81  | 0.000 |
| LPI                | 0.183     | 213 | 0.000 | 0.880 | 213 | 0.000 |

a. Lilliefors Significance Correction
Therefore, the two dimensions can explain 57% of data variability; Dimension 1 contributed 34.7% of inertia, and Dimension 2 contributed 22.3% (Table 3).

Regarding the low values (α < 0.7) of Cronbach’s Alpha, for both dimensions they are acceptable at an exploratory analysis context (Field, 2013; Hair et al., 2013; Nunnally, 1978), especially since alpha is a measure of internal consistency, and this particular measure is not to be met with a high value in a diverse dataset; such as the present study that includes data from two phenomena. Furthermore, MCA in the present study is not conducted in view of producing synthetic/latent variables or factors from the variables included in the analysis. Hence, the low alpha values are irrelevant to the scope of the present research.

From the pattern exhibited in Fig. 3, it becomes apparent that Dimension 1 is a prime indicator for imports and exports variables while the investment variable has little contribution to the model. Dimension 2 is a prime indicator for mortality and recovery data, as well as for transportation variables. As per Hoffman and De Leeuw (1992), the longer the lines converge towards each axis, the better the discrimination measures at MCA. Based on this analysis, Dimension 1 can be expressed as the ‘imports and exports’ dimension. From the examination of the Joint plot (Fig. 4) one can extract agglomerations and/or groups of variables. Proximity between the items indicates that the variables are associated. The variables’ categories of COVID-19 data mortality and recovery aggregate in two proximate groups. The first group, with higher values towards the right, is formed by the category points indicating greater mortality (>0.0162) and lower recovery (≤0.8611), while the other group is positioned at the lower left of the Joint plot, indicating lower mortality and greater recovery.

The variables of imports and exports also gather in two proximate groups. One group, farthest to the right, is formed by the category points indicating lower imports (≤44,335) and exports (≤37,704), while the other group, towards the left, indicates greater imports and exports. In addition, the variables of LPI and investment appear to be associated with imports and exports, respectively (as is probably expected, as they are all transportation variables). Hence, the variable of transportation investment appears to be associated with variables’ categories of lower imports and lower exports. Since the investment variable has a lower discrimination measure at MCA (Hoffman and De Leeuw, 1992), it is not a coincidence that both variables’ categories lie close to each other. To this extent, the transportation variables of imports, exports, and LPI indicate that greater values were associated with greater recovery and lower mortality rates. This can lead to the conclusion that not only transportation and epidemiological variables are indeed associated, but countries with higher transportation intensity, and thus, more elaborate transportation systems, are better equipped in dealing with the COVID-19 pandemic since these countries are exhibiting better recovery and lower mortality rates.

4.3. Crosstabulation

The sample consists of data referring to imports and exports of countries, the logistics performance index, and investment in transportation, versus epidemiological data (mortality and recovery rates). For both sets of variables (transportation and viral dynamics) the variables are dependent, as what happens in one country is dependent upon what happens to another country (a stepping-stone of transportation itself and a prerequisite of virology). From these continuous variables, dichotomous categorical variables are generated based on the calculation of averages. The utilization of the average for every variable enables the creation of classes, and thus the generation of the contingency tables (as included in Appendix C). From these contingency tables one can proceed with the statistical decision test(s) to investigate any association of the variables, as well as the calculation(s) of statistical power. An indicative crosstab is included in Table 4 for demonstrative purposes. The count ‘a’ designates the number of countries that are above the world average in Variable I (pandemic data) and Variable II (transportation data). Count ‘b’ designates the cases of countries where the Variable II is over the world average, but Variable I is less than the world average. In the same manner, counts ‘c’ and ‘d’ compile the crosstab.

For the statistical decision test, the marginal probabilities of the crosstab are calculated. Given the dependent nature of the dataset, McNemar’s test, whose null hypothesis considers marginal homogeneity of the contingency table(s), should be utilized. The rejection of the null hypothesis provides statistical significance to the results, implying statistical association (albeit causal or not) of the variables. Nonetheless, statistical significance of the test is not a definitive indicator of causality. Thereby, the rejection of the null hypothesis signifies that the variables are associated, i.e., that mortality and recovery rates from the coronavirus are associated with transportation, as reflected in the markers of trade, logistics, and transportation investment. It should be noted that statistical significance does not provide any proof that transportation is indeed the factor that triggers changes in mortality and recovery rates. As to the latter, more research is required. This would materialize from causal inference, where the causal association of the variables is investigated (Bonita et al., 2006; U.S. Department of Health and Human Services Centers for Disease Control and Prevention, 2006). The results of McNemar’s test are included in Table 5.

As the p-value of McNemar’s test for all contingency tables stands at ‘Exact Signature’ = P-value < α = 5%, the results of the statistical hypothesis tests are statistically significant (given that one has selected a significance level of five percent); for these variables, the null hypothesis of marginal homogeneity is rejected. With these results, the analysis delivers strong evidence that the variables are

| Table 3 | The MCA model summary (source: Authors). |
|-------------------------------------------------
| Cronbach’s Alpha | Eigenvalue | Inertia | % of variance |
| Dimension 1 | 0.623 | 2.081 | 0.347 | 34.70% |
| Dimension 2 | 0.303 | 1.337 | 0.223 | 22.30% |
| Total | – | 3.418 | 0.570 | – |
associated. Thus, the work herein replicates the association of transportation (as a mirrored effect and derived externality from trade intensity, logistics performance, and investment in transportation) with epidemiological data. These results provide a stepping-stone for further research, to strenuously examine said correlation and (any potential) causality between the variables, for the association between these variables can bear important contributions to the literature, as the instance of transportation as a vector of pandemics is replicated.

The reliability (statistical power) of the data is computed (Dai and Zheng, 2017; Hedges and Rhoads, 2010; Nuzzo, 2016) in the form of the probability of correctly rejecting the null hypothesis when the alternative hypothesis is true (the complement of a Type II error). This power analysis is calculated retrospectively (post hoc) to evaluate the power achieved with the actual sample of the study. Said power results in values ranging from 63.77% (the only value under 80%—the academic benchmark for statistical power) to 100%. Seven out of the eight tests bear a statistical power of over 80% (the complete post hoc statistical power calculations can be accessed in Appendix C), values that are considered very high (Verma and Goodale, 1995).

There is also a test that portrays statistical significance (Transportation investment and Recovery), but due to the arrangement of

Fig. 3. Discrimination measures (source: Authors, IBM SPSS™ output).

Fig. 4. Joint plot (source: Authors, MS Excel™ output).
the crosstab (the possibility of Investment = HIGH and Recovery = LOW included zero cases, as there is no country with higher than average transportation investment and lower than average recovery rates – an interesting discovery nonetheless), the power calculation cannot proceed (as OR = 0); for this variable, the power of the test is inconclusive, but for the approximation of one case where there is none, a very high statistical power is achieved; of course, this result is indicative (and in italics in Table 5), as statistical power cannot be computed for an odds ratio of zero. For the calculation of achieved power, the assumption may not introduce significant bias. This fact is reinforced by the a priori calculation of sample size, where the minimum sample size for an achieved power of 80% is \( N = 39 \) (Table 6). As the actual sample size is \( N = 56 \), it could be deduced that a very high statistical power is indeed achieved for this test.

Therefore, for the analysis conducted, one can consider the power of the test more than adequate and the subsequent validity and reliability of the results same. As the statistical power of the study, i.e., its ability to detect a factual eventuality, is more than acceptable, the present analysis has a very high probability to correctly reject the null hypothesis and a very low probability of a Type II error.

### Table 4
Framework of the crosstab, McNemar’s test, and the specifics of the statistical power calculation (source: Authors).

| Variable 2 | Total |
|-----------|-------|
| High      | Low   |
| Count     | \( a \) | \( b \) | \( a + b \) |
| \% of Total | \( \pi_{11} \) | \( \pi_{12} \) | \( \pi_t \) |
| Low       | \( c \) | \( d \) | \( c + d \) |
| Count     | \( \pi_{21} \) | \( \pi_{22} \) | \( 1 - \pi_t \) |

### Chi-Square Test
**Null hypothesis**

\( \pi_{12}/\pi_{21} = 1 \)

**Alternative Hypothesis**

\( \pi_{12}/\pi_{21} \neq 1 \)

**Statistical Power calculations**

(Heinrich Heine University Düsseldorf, 2020)

The probability \( \pi_D \) of discordant pairs

\( \pi_D = \pi_{12} + \pi_{21} \)

Odds Ratio (OR)

\( \text{OR} = \pi_{12}/\pi_{21} \)

### Table 5
The results of McNemar’s test and computed statistical Power (source: Authors, IBM SPSS™ output).

| Variables cross-tabulated (factor/condition) | P-value | Power (1-\( \beta \) err prob) |
|---------------------------------------------|---------|-------------------------------|
| Imports/Recovery                            | 0.000   | 99.97%                        |
| Imports/Mortality                           | 0.000   | 100.00%                       |
| Exports/Recovery                            | 0.010   | 63.77%                        |
| Exports/Mortality                           | 0.000   | 99.23%                        |
| Logistics performance/Mortality             | 0.001   | 86.54%                        |
| Logistics performance/Recovery              | 0.000   | 100.00%                       |
| Transportation investment/Mortality          | 0.000   | 99.99%                        |
| Transportation investment/Recovery          | 0.000   | 95.69% (approx.)              |

### Table 6
A priori sample size calculation for Transportation investment and Recovery (source: Authors, G*Power™ output).

| Exact - Proportions: Inequality, two dependent groups (McNemar) |
|---------------------------------------------------------------|
| **Analysis:** A priori: Compute required sample size          |
| **Input:** Tail(s) = Two                                      |
| Odds ratio = 0.2777160                                        |
| \( \alpha \) err prob = 0.05                                  |
| Power (1-\( \beta \) err prob) = 0.80                        |
| Prop discordant pairs = 0.643                                 |
| **Output:** Lower critical N = 7.00000000                     |
| Upper critical N = 18.00000000                                |
| Total sample size = 39                                       |
| Actual power = 0.8425005                                      |
| Actual \( \alpha \) = 0.0432853                                 |
| Proportion \( p_{12} = 0.1397583 \)                          |
5. Discussion and conclusions

The transportation sector has in recent centuries witnessed evolution that can only be expressed adequately not as evolution per se, but as revolution. Innovation, efficiency, advances in technology, international collaboration, international law, and common safety and quality standards have all undergone transformations that relinquish a global and quasi-seamless transportation supersystem. Yet, amidst all these advances, the global distribution of pathogens through transportation has only been exacerbated, as the same factors that facilitate the continuum of the hinterlands and the forelands, are the ones inflaming pathogen distribution. The latter stands, of course, should preventative measures fail or even worse, be not in place at all. Some decades ago, one would not have even dared to dream of ‘in-transit visibility’ of cargo through a personal handheld device, real-time and with access from an abundance of locations. At the same time, pandemic dynamics remain as potent as ever, lest the world has forgotten the importance of prevention, as if the significance of public health could somehow have excluded the transportation sector (Mackett and Thoreau, 2015).

Public health pertains to a domain to which humanity owes an extensive debt of gratitude, yet one that requires miscellaneous aspects to function in unison, such as inclusion and community engagement (White et al., 2020; Yuan et al., 2021). The presence of public health concepts as embedded in transportation systems is a prerequisite of the latter’s sustainability. As exhibited perfectly in the most recent coronavirus pandemic, the absence of preventative measures rooted in functional public-health-oriented systems entails a higher cost for societies compared to the offset of deploying public health mandates; not to mention the toll in human lives. The recent pandemic stands as yet another wake-up call for indeed all society due to the imperative nature of including public health allowances in our societal fabric, and especially owing to functions that pertain to global pathogen distribution mechanisms, such as transportation. The latter has for centuries been considered the actual (although latent) vector of pathogens, though, even in all the revolutions witnessed in modern systems of global logistics, transportation systems do not include public health planning as a prerequisite in their conception. This research constitutes a reminder that one of the major preventative measures that can be put in place in society refers to appending public health within transportation, redefining even the primary facets of supply chains, so that mobility can act as a deterrent of disease through a culture of prevention, rather than a vector of disastrous consequences.

As such, this work belongs to the domain of replication studies, as the role of transportation as a pathogen vector is beyond dispute. Replication studies (Bonett, 2020; Spector et al., 2014) can be witnessed in a plethora of domains, including mathematics (Aguilar, 2020), education (Morrison, 2019), economics (Mueller-Langer et al., 2019), business (Harzing, 2016), and social and behavioural sciences (Mishra et al., 2017). These types of studies are important, since, especially within a crisis, the plethora of miscommunication can blur the societal compass. Replication assists in reminding us that there are still latent dynamics in place that in essence govern and dictate the outcome of a crisis. Especially with reference to the recent pandemic, there is no doubt that mobility holds the lion’s share of responsibility, and that the global transportation and logistics network has only exacerbated the problem. Exactly here can a replication study as this, point to the dire need of a new paradigm for transportation, one that is laid on the foundation of health, resilience, and sustainability.

The work herein replicates the correlation of transportation with reference to virology dynamics, such as recovery and mortality rates. It does so through compiling contingency tables from imports and exports data, the logistics performance index, and transportation investment data, to investigate these variables’ association with epidemiological data as portrayed within mortality and recovery rates. The indicators selected are indicative of many aspects of transportation, such as trade intensity, the amount of investment in transportation systems, and the quality of logistics systems. As transportation can be manifested in a variety of expressions, these markers were selected as indicative. Of course, future research can investigate the correlation of epidemiological data with other variables pertinent to transportation. Through the compilation of the contingency tables, the model of the study can proceed to statistical hypothesis testing.

In this work, the bivariate analysis of crosstabulation and the MCA approach were used to explore the relationship between transportation intensity factors (including imports, exports, investments, and logistics performance) and the COVID-19 pandemic mortality and recovery rates. From the MCA approach the results revealed that countries with higher imports and exports seem to be better equipped in dealing with the COVID-19 pandemic since they are showing better recovery rates and lower mortality rates. This is a very important finding, as this methodology provides not only strong evidence of association between the transportation and pandemic variables, but indications of specific trends as well. As a step towards further research, more variables could be incorporated in the model to investigate the manifestation of a richer collection of clusters (or their absence).

As the variables are not independent of each other, both within and across groups, a suitable test applicable to dependent data is selected to examine the association of the variables and this pertains to McNemar’s test for dependent categorical data. In addition, as an indicator of the validity and reliability of the results of the test, statistical power is calculated to indicate the probability of Type II error. The statistical hypothesis test employed demonstrates statistical significance among all the variables selected pertaining to transportation and the pandemic. In addition, the statistical power of the tests is very high, hinting to the very low probability of incorrectly rejecting a true null hypothesis. The methodological formulation of this work is portrayed in Fig. 5.

5.1. Implications for policy and practice

As mentioned, the replication of the association of transportation with pandemics may facilitate the process towards the direction of sustainable transportation, as these results pertain to important policy externalities (Banister 2008; Balsas 2003; Bertolini et al., 2005; Fahirinia et al., 2018; Lucas 2012; Tang and Veeleenturf 2019). Indeed, the association of transportation and the pandemic may
stand to remind society that there is a need of reimplementing public health directions in the very framework of the global logistics network. Transportation itself is manifested because of policy, and it has come a long way due to international collaboration, as exhibited in international law and the widely accepted and adhered to international standards of all transportation industries. However, the aspect of transport systems’ safety surfaces indicatively in these times, due not to a disaster that cripples the transportation systems thus leading to disastrous outcomes, but to disastrous outcomes that are a direct result of the effectiveness of the global transportation system. There is a need towards a holistic approach with respect to the governance of transport systems of the future, one directed towards a preventative framework, which will not be able to exacerbate outbreaks of any disease, simply because the system will be based on public health safeguards.

At the same time, transportation is a major source of pollution and all systems of mobility go to dissipate contaminants and pathogens. Thereby, the impact of transportation on health must be tackled in a plethora of ways, as transportation can act both as a creator and as an agent of pollution. To only make matters worse, the fact that the scope and function of transportation are international, only comes to veil any approach in mitigation. Many societal systems may be able to monitor an activity of a particular entity and retract an action, but when the entity spans across the globe, in far away and barren lands, up in the sky, and in the middle of the ocean, it is extremely difficult to monitor, control, and assess environmental impact, not to mention enforce environmental and health mandates. At the same time, it is even more difficult to ensure that systems will function as they should, as transportation pertains to international law that, as soft law, is based on collaboration and not on enforcement. This is why humanity has transformed its oceans in toxic soups, when at the same time it is forced to endure the fact that the right to clean water and air is not universal. The importance of the externalities of transportation with reference to health is indicatively exhibited when a crisis is under way. Of course, the solution is not to retrench, but to create a system of mobility that is factually based on health, whereupon the transportation industries will be able to self-regulate. And, here, international collaboration and law, national policy, and governance pertain to crucial rudiments of this endeavour’s effectiveness.

In addition, research replicating the impact of transportation in pandemics has managerial implications, as firms may yet be reminded of the importance of systems that function with a baseline of health. Thus, an efficient culture of mutualism and sustainability-based prosperity can be instituted, and not one based on minimizing accounting cost and at the same time disregarding social, environmental, and health costs. Practice is also able to utilize the methodology followed herein to investigate the correlation and dependence of variables in an ad hoc basis, as the analytical instrument does not presuppose the selection of a particular variable. As such, the methodological formulation can be of value to managerial practice, independently of the distinct variables utilized in the present work.

The sector regarding the governance of transport systems bears indicative potential for growth and innovation. It is exactly here that society can place a stake not only in preventing the next pandemic but also in establishing a global system of mobility that will not pollute the environment and will not bear the toll of threatening the diversity of our natural habitats. This is the future, and clearly policy has a major role to play if one is referring to a future of which we will be proud to be a part. Notwithstanding, effective policy can facilitate the emergence of a functional transport system that provides mobility without costing society so much in spillover and lateral health costs, pandemics included.

Fig. 5. The analytical framework of this study (Source: Authors, MS Visio™ output).
5.2. Limitations and implications for future research

Through this paper, what is scrutinized and replicated is the correlation of transportation and disease with recent (inclusive of January 2021) epidemiological data from the coronavirus pandemic and longitudinal data that mirrors transportation intensity; this data includes the markers of trade (imports and exports), logistics performance, and transportation investment (with private participation). In addition, the methodology employed can service the investigation of the correlation of many more variables pertinent to transportation and pandemics. Future research will hopefully provide more insight as to the mechanism of potential causality between the variables (Bonita et al., 2006; U.S. Department of Health and Human Services Centers for Disease Control and Prevention, 2006), as the present study provides strong evidence of correlation and dependence of the variables, but not causality, and the latter can be extremely different from the former. A variable that may pose as an effect to a condition (and possibly among many other effects) may not serve as an instigator of causality for said condition. Further research will be able to uncover any such mechanism through the process of causal inference. Therefore, further research can stem from this work, as etiology of the factors can be investigated. The replication aspect of this study has been achieved with the rejection of the null hypothesis of independence. However, it would be intriguing to investigate potential causality of the variables, as association has already been extracted. Via the methodological formulation of causal inference, novel insight can be granted with reference to the dynamics that solidify the correlation of transportation and viral incidence. This process can be the objective of a plethora of future research, as it regards an intricate and elaborate process to extract the exact mechanism of causality, if any. Results in any direction would, of course, be of importance.

At the same time, the model and methodology can pertain to the baseline for more research, as they present an analytical blueprint to employ crosstabulation and statistical decision tests in tandem with MCA for the investigation of correlation of variables of interest. The methodology can transform a variable from the analog and continuous universe to a dichotomous manifestation that will compile a crosstab. From said crosstab, statistical decision theory can be employed, and strong evidence of correlation and dependence can be delivered. At the same time, an army of indicators can be produced (such as measures of association), which are to document the exact type of correlation among the variables.

This work does entail limitations, as any model formulation would. The transformation of the variables itself refers to a modelling allowance, since a continuous phenomenon is portrayed as dichotomic. It is, of course, in the interest of the analysis to utilize crosstabs, seeing that they are a versatile and simple instrument that can produce an unambiguous result that answers the research question. Nonetheless, one must bear in mind that this is a model, and like all models, only provides an approximation of reality. Although for the phenomenon under investigation, and especially since the correlation of the variables of transportation and pandemics does not occur here for the first time, one can observe that the model is actually able to replicate a known phenomenon. As such, it can be inferred that the model approximates reality in an effective manner. The very high power of the statistical decision tests reinforces this position.

In the time of writing this the results of the pandemic have not been expressed in their full might, as one can but ponder the volatility of the next day for many societal systems, including transportation. At the same time, the fact that the recent plunge in production, transportation, and trade has subsequently slashed pollution in many regions (Perera et al., 2021; Venter et al., 2021) cannot make society acquiesce, as the ultimate goal is to attain growth in a sustainable manner, not to celebrate the positive exter.

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Appendix A

Imports of goods and services (% of GDP)

"Imports of goods and services represent the value of all goods and other market services received from the rest of the world. They include the value of merchandise, freight, insurance, transport, travel, royalties, license fees, and other services, such as communication, construction, financial, information, business, personal, and government services. They exclude compensation of employees and investment income (formerly called factor services) and transfer payments.

- ID: NE. IMP.GNFS.ZS
- Source: World Bank national accounts data, and OECD National Accounts data files: https://data.worldbank.org/indicator/NE.IMP.GNFS.ZS?view=chart
- License: CC BY-4.0
• Aggregation Method: Weighted Average”

Exports of goods and services (% of GDP)

“Exports of goods and services represent the value of all goods and other market services provided to the rest of the world. They include the value of merchandise, freight, insurance, transport, travel, royalties, license fees, and other services, such as communication, construction, financial, information, business, personal, and government services. They exclude compensation of employees and investment income (formerly called factor services) and transfer payments.

• ID: NE. EXP.GNFS.ZS
• Source: World Bank national accounts data, and OECD National Accounts data files: https://data.worldbank.org/indicator/NE.EXP.GNFS.ZS?view=chart
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Logistics performance index: quality of trade and transport-related infrastructure

“Data are from Logistics Performance Index surveys conducted by the World Bank in partnership with academic and international institutions and private companies and individuals engaged in international logistics. 2009 round of surveys covered more than 5000 country assessments by nearly 1000 international freight forwarders. Respondents evaluate eight markets on six core dimensions on a scale from 1 (worst) to 5 (best). The markets are chosen based on the most important export and import markets of the respondent’s country, random selection, and, for landlocked countries, neighbouring countries that connect them with international markets. Details of the survey methodology are in Arvis and others’ Connecting to Compete 2010: Trade Logistics in the Global Economy (2010). Respondents evaluated the quality of trade and transport related infrastructure (e.g., ports, railroads, roads, information technology), on a rating ranging from 1 (very low) to 5 (very high). Scores are averaged across all respondents.

• ID: LP. LPI.INFR.XQ
• Source: World Bank and Turku School of Economics, Logistic Performance Index Surveys. Data are available online at: https://data.worldbank.org/indicator/LP.LPI.INFR.XQ
• Summary results are published in Arvis and others’ Connecting to Compete: Trade Logistics in the Global Economy, The Logistics Performance Index and Its Indicators report.
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Investment in transport with private participation (current US$)

“Investment in transport projects with private participation refers to commitments to infrastructure projects in transport that have reached financial closure and directly or indirectly serve the public. Movable assets and small projects are excluded. The types of projects included are management and lease contracts, operations and management contracts with major capital expenditure, greenfield projects (in which a private entity or a public-private joint venture builds and operates a new facility), and divestitures. Investment commitments are the sum of investments in facilities and investments in government assets. Investments in facilities are the resources the project company commits to invest during the contract period either in new facilities or in expansion and modernization of existing facilities. Investments in government assets are the resources the project company spends on acquiring government assets such as state-owned enterprises, rights to provide services in a specific area, or the use of specific radio spectrums. Data are in current U.S. dollars.

• ID: IE. PPI.TRAN.CD
• Source: World Bank, Private Participation in Infrastructure Project Database (ppi.worldbank.org): “https://data.worldbank.org/indicator/IE.PPI.TRAN.CD” https://data.worldbank.org/indicator/IE.PPI.TRAN.CD
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Appendix B

Descriptive statistics, histograms, and boxplots of the variables are as follows.
### Table 7
Descriptive statistics for COVID-19 Mortality and Recovery (source: Authors, IBM SPSS™ output).

| Descriptives | Statistic      | Std. Error     |
|--------------|----------------|----------------|
| **Mortality** |                |                |
|              | Mean           | 0.0199328602   | 0.00187038704 |
|              | 95% Confidence Interval for Mean | | |
|              | Lower Bound    | 0.0162464091   |  | |
|              | Upper Bound    | 0.0236193113   |  | |
|              | 5% Trimmed Mean| 0.0164298198   |  | |
|              | Median         | 0.0153935380   |  | |
|              | Variance       | 0.001          |  | |
|              | Std. Deviation | 0.02761593367  |  | |
|              | Minimum        | 0.00000000     |  | |
|              | Maximum        | 0.28977273     |  | |
|              | Range          | 0.28977273     |  | |
|              | Interquartile Range | 0.01740206 | | |
|              | Skewness       | 6.425          | 0.165  | |
|              | Kurtosis       | 54.545         | 0.328  | |
| **Recovery** |                |                |
|              | Mean           | 0.7882986868   | 0.01440569077 |
|              | 95% Confidence Interval for Mean | | |
|              | Lower Bound    | 0.7599056998   |  | |
|              | Upper Bound    | 0.8166916738   |  | |
|              | 5% Trimmed Mean| 0.8142467712   |  | |
|              | Median         | 0.8452795055   |  | |
|              | Variance       | 0.045          |  | |
|              | Std. Deviation | 0.21269747534  |  | |
|              | Minimum        | 0.00000000     |  | |
|              | Maximum        | 1.00000000     |  | |
|              | Range          | 1.00000000     |  | |
|              | Interquartile Range | 0.20364944 | | |
|              | Skewness       | –1.895         | 0.165  | |
|              | Kurtosis       | 3.611          | 0.328  | |

### Table 8
Descriptive statistics for Exports (source: Authors, IBM SPSS™ output).

| Descriptives | Statistic      | Std. Error     |
|--------------|----------------|----------------|
| **EXP**      |                |                |
|              | Mean           | 42.10792951    | 1.929851926 |
|              | 95% Confidence Interval for Mean | | |
|              | Lower Bound    | 38.30615686    |  | |
|              | Upper Bound    | 45.90970216    |  | |
|              | 5% Trimmed Mean| 38.41634834    |  | |
|              | Median         | 33.60831788    |  | |
|              | Variance       | 890.115        |  | |
|              | Std. Deviation | 29.837886754   |  | |
|              | Minimum        | 7.189963       |  | |
|              | Maximum        | 201.435817     |  | |
|              | Range          | 194.245855     |  | |
|              | Interquartile Range | 25.539274 | | |
|              | Skewness       | 2.717          | 0.157  | |
|              | Kurtosis       | 10.049         | 0.314  | |

### Table 9
Descriptive statistics for Imports (source: Authors, IBM SPSS™ output).

| Descriptives | Statistic      | Std. Error     |
|--------------|----------------|----------------|
| **IMP**      |                |                |
|              | Mean           | 47.4836        | 1.78870    |
|              | 95% Confidence Interval for Mean | | |
|              | Lower Bound    | 43.9599        |  | |
|              | Upper Bound    | 51.0073        |  | |
|              | 5% Trimmed Mean| 44.4419        |  | |
|              | Median         | 39.6684        |  | |
|              | Variance       | 764.667        |  | |
|              | Std. Deviation | 27.65261       |  | |
|              | Minimum        | 12.92          |  | |
|              | Maximum        | 198.76         |  | |
|              | Range          | 185.83         |  | |
|              | Interquartile Range | 29.70 | | |
|              | Skewness       | 2.160          | 0.157  | |
|              | Kurtosis       | 6.663          | 0.314  | |
Table 10
Descriptive statistics for Investment in transportation (source: Authors, IBM SPSS™ output).

| Descriptives                  | Statistic     | Std. Error     |
|-------------------------------|---------------|----------------|
| INV Mean                      | 5366781956.0012 | 1181151826.86951 |
| 95% Confidence Interval for Mean Lower Bound | 3016214910.4008 |
| Upper Bound                   | 7717349001.6016 |
| 5% Trimmed Mean               | 3569093902.4952 |
| Median                        | 5444200000.0000 |
| Variance                      | 113004690687491650000.000 |
| Std. Deviation                | 10630366441.82595 |
| Minimum                       | 2.65E-7 |
| Maximum                       | 4.49E+10 |
| Range                         | 44484325000.00 |
| Interquartile Range           | 4447465000.00 |
| Skewness                      | 2.662 |
| Kurtosis                      | 6.640 |

Table 11
Descriptive statistics for the Logistics performance index (source: Authors, IBM SPSS™ output).

| Descriptives                  | Statistic     | Std. Error     |
|-------------------------------|---------------|----------------|
| LPI Mean                      | 2.64812986    | 0.042571394    |
| 95% Confidence Interval for Mean Lower Bound | 2.56421241 |
| Upper Bound                   | 2.73204732 |
| 5% Trimmed Mean               | 2.60993303 |
| Median                        | 2.45119100 |
| Variance                      | 0.386          |
| Std. Deviation                | 0.621309034   |
| Minimum                       | 1.602286 |
| Maximum                       | 4.320442 |
| Range                         | 2.718156 |
| Interquartile Range           | 0.803027 |
| Skewness                      | 1.061 |
| Kurtosis                      | 0.196 |

Fig. 6. Histogram of COVID-19 mortality (source: Authors, IBM SPSS™ output).
Fig. 7. Boxplot of COVID-19 mortality (source: Authors, IBM SPSS™ output).

Fig. 8. Histogram of COVID-19 recovery (source: Authors, IBM SPSS™ output).
Fig. 9. Boxplot of COVID-19 recovery (source: Authors, IBM SPSS™ output).

Fig. 10. Histogram for Exports (source: Authors, IBM SPSS™ output).
Fig. 11. Boxplot for Exports (source: Authors, IBM SPSS™ output).

Fig. 12. Histogram for Imports (source: Authors, IBM SPSS™ output).
Fig. 13. Boxplot for Imports (source: Authors, IBM SPSS™ output).

Fig. 14. Histogram for Investment in transportation (source: Authors, IBM SPSS™ output).
Fig. 15. Boxplot for Investment in transportation (source: Authors, IBM SPSS™ output).

Fig. 16. Histogram of the Logistics performance index (source: Authors, IBM SPSS™ output).
Appendix C

The crosstabulation of the variables and the analytical calculation of statistical power can be accessed in the following Tables.

Table 12
Imports * Recovery Crosstabulation (source: Authors, IBM SPSS™ output).

|       | Recovery |       |       |       |       |
|-------|----------|-------|-------|-------|-------|
|       |          | High  | Low   | Total |
| Imports|          |       |       |       |
| High   | Count    | 24    | 3     | 27    |
|        | % of Total| 15.7% | 2.0%  | 17.6% |
| Low    | Count    | 31    | 95    | 126   |
|        | % of Total| 20.3% | 62.1% | 82.4% |
| Total  | Count    | 55    | 98    | 153   |
|        | % of Total| 35.9% | 64.1% | 100.0%|

Chi-Square Tests

|       | Value | Exact Sig. (2-sided) |
|-------|-------|-----------------------|
| McNemar’s Test |       | 0.000⁴               |
| No. of valid cases | 153     |                       |
| a. Binomial distribution used. |

Fig. 17. Boxplot of the Logistics performance index (source: Authors, IBM SPSS™ output).
Table 13
Imports * Recovery achieved power (source: Authors, G*Power™ output).

| Analysis:       | Post hoc: Compute achieved power |
|-----------------|----------------------------------|
| Input:          |                                  |
| Tail(s)         | Two                              |
| Odds ratio      | 0.09852217                      |
| α err prob      | 0.05                             |
| Total sample size | 153                            |
| Prop discordant pairs | 0.20706          |
| Output:         |                                  |
| Lower critical N | 9.0000000                      |
| Upper critical N | 23.0000000                     |
| Power (1-β err prob) | **0.9996600**                |
| Actual α        | 0.0200616                       |
| Proportion p₁₂  | 0.0185704                       |

Proportion p₂₁ = 0.1884896

Table 14
Imports * Mortality crosstabulation (source: Authors, IBM SPSS™ output).

| Mortality | Total |
|-----------|-------|
|           | High  | Low  |     |
| Imports   |       |      |     |
| High      | 43    | 82   | 125 |
| % of Total| 28.1% | 53.6% | 81.7% |
| Low       | 12    | 16   | 28  |
| % of Total| 7.8%  | 10.5% | 18.3% |
| Total     | 55    | 98   | 153 |
| % of Total| 35.9% | 64.1% | 100.0% |

Chi-Square Tests

| McNemar’s Test | Value | Exact Sig. (2-sided) |
|----------------|-------|----------------------|
| No. of valid cases | 153   | 0.000^a             |
| a. Binomial distribution used. |

Table 15
Imports * Mortality achieved power (source: Authors, G*Power™ output).

| Analysis:       | Post hoc: Compute achieved power |
|-----------------|----------------------------------|
| Input:          |                                  |
| Tail(s)         | Two                              |
| Odds ratio      | 6.871794                        |
| α err prob      | 0.05                             |
| Total sample size | 153                            |
| Prop discordant pairs | 0.577808          |
| Output:         |                                  |
| Lower critical N | 34.0000000                     |
| Upper critical N | 55.0000000                     |
| Power (1-β err prob) | **1.0000000**                |
| Actual α        | 0.0334167                       |

Proportion p₁₂ = 0.5044057
Table 16
Exports * Recovery crosstabulation (source: Authors, IBM SPSS™ output).

|                | Recovery |       | Total |
|----------------|----------|-------|-------|
|                | High     | Low   |       |
| Exports        |          |       |       |
| High           | Count    | 79    | 20    | 99    |
| % of Total     | 51.6%    | 13.1% | 64.7% |
| Low            | Count    | 41    | 13    | 54    |
| % of Total     | 26.8%    | 8.5%  | 35.3% |
| Total          | Count    | 120   | 33    | 153   |
| % of Total     | 78.4%    | 21.6% | 100.0%|

Chi-Square Tests

| McNemar's Test | Value | Exact Sig. (2-sided) |
|----------------|-------|----------------------|
| No. of valid cases | 153   | 0.010<sup>a</sup>   |
| a. Binomial distribution used. |

Table 17
Exports * Recovery achieved power (source: Authors, G*Power™ output).

| Exact - Proportions: Inequality, two dependent groups (McNemar) |
|---------------------------------------------------------------|
| **Analysis:** Post hoc: Compute achieved power               |
| **Input:**                                                   |
| Tail(s) = Two                                               |
| Odds ratio = 0.488056                                       |
| α err prob = 0.05                                           |
| Total sample size = 153                                     |
| Prop discordant pairs = 0.303108                             |
| **Output:**                                                 |
| Lower critical N = 16.0000000                                |
| Upper critical N = 31.0000000                                |
| **Power (1-β err prob) = 0.6377385**                        |
| Actual α = 0.0399861                                        |
| Proportion p_{12} = 0.0994141                                |
| Proportion p_{21} = 0.2036939                                |

Table 18
Exports * Mortality crosstabulation (source: Authors, IBM SPSS™ output).

|                | Mortality |       | Total |
|----------------|-----------|-------|-------|
|                | High      | Low   |       |
| Exports        |           |       |       |
| High           | Count     | 29    | 70    | 99    |
| % of Total     | 19.0%     | 45.8% | 64.7% |
| Low            | Count     | 25    | 29    | 54    |
| % of Total     | 16.3%     | 19.0% | 35.3% |
| Total          | Count     | 54    | 99    | 153   |
| % of Total     | 35.3%     | 64.7% | 100.0%|

Chi-Square Tests

| McNemar's Test | Value | Exact Sig. (2-sided) |
|----------------|-------|----------------------|
| No. of valid cases | 153   | 0.000<sup>a</sup>   |
| a. Binomial distribution used. |
Table 19  
Exports * Mortality achieved power (source: Authors, G*Power™ output).

| Analysis: | Post hoc: Compute achieved power |
|----------|---------------------------------|
| Input:   |                                  |
| Tail(s)  | Two                             |
| Odds ratio | 2.8098                         |
| α err prob | 0.05                           |
| Total sample size | 153                           |
| Prop discordant pairs | 0.5327                     |
| Output:  |                                  |
| Lower critical N | 31.00000000             |
| Upper critical N | 51.00000000             |
| Power (1-β err prob) | **0.9922814**             |
| Actual α | 0.0352414                       |
| Proportion p_{12} | 0.3928764                    |
| Proportion p_{21} | 0.1398236                    |

Table 20  
Logistics performance index * Mortality crosstabulation (source: Authors, IBM SPSS™ output).

|        | Mortality |      |        |      |      | Total |      |      |      |      |      |      |
|--------|-----------|------|--------|------|------|-------|------|------|------|------|------|------|
|        | High      | Low  | % of Total | High | Low  | % of Total | Total |      |      |      |      |      |
| LPI    | High      |      |            |      |      |        |      |      |      |      |      |      |
|        | Count     |      | % of Total |      |      |        |      |      |      |      |      |      |
|        | 38        |      | 26.2%     | 54   |      | 37.2%     | 92   |      |      |      |      |      |
|        |           |      | (% of Total |      |      |        |      |      |      |      |      |      |
|        | Low       |      |            |      |      |        |      |      |      |      |      |      |
|        | Count     |      | % of Total |      |      |        |      |      |      |      |      |      |
|        | 24        |      | 16.6%     | 29   |      | 20.0%     | 53   |      |      |      |      |      |
|        |           |      | (% of Total |      |      |        |      |      |      |      |      |      |
| Total  | Count     |      |            |      |      |        |      |      |      |      |      |      |
|        | 62        |      | 42.8%     | 83   |      | 57.2%     | 145  |      |      |      |      |      |

Chi-Square Tests

| Value | Exact Sig. (2-sided) | 0.001* |
|---|----------------------|-------|
| McNemar's Test | No. of valid cases | 145 |
| a. Binomial distribution used. | | |

Table 21  
Logistics performance index * Mortality achieved power (source: Authors, G*Power™ output).

| Analysis: | Post hoc: Compute achieved power |
|----------|---------------------------------|
| Input:   |                                  |
| Tail(s)  | Two                             |
| Odds ratio | 2.24096385                     |
| α err prob | 0.05                           |
| Total sample size | 145                           |
| Prop discordant pairs | 0.433752             |
| Output:  |                                  |
| Lower critical N | 23.00000000             |
| Upper critical N | 40.00000000             |
| Power (1-β err prob) | **0.8653770**             |
| Actual α | 0.0429565                       |
| Proportion p_{12} | 0.2999177                    |

Table 22  
Logistics performance index * Recovery crosstabulation (source: Authors, IBM SPSS™ output).

|        | Recovery |      |        |      |      | Total |      |      |      |      |      |      |
|--------|----------|------|--------|------|------|-------|------|------|------|------|------|------|
|        | High     | Low  | % of Total | High | Low  | % of Total | Total |      |      |      |      |      |
|        | Count    |      | % of Total |      |      |        |      |      |      |      |      |      |
| LPI    | High     |      |            |      |      |        |      |      |      |      |      |      |
|        | 39       |      | 27.5%     | 9    |      | 6.3%     | 48   |      |      |      |      |      |
|        |           |      | (% of Total |      |      |        |      |      |      |      |      |      |
|        | Low      |      |            |      |      |        |      |      |      |      |      |      |
|        | Count    |      | % of Total |      |      |        |      |      |      |      |      |      |
|        | 71       |      | 50.0%     | 23   |      | 16.2%     | 94   |      |      |      |      |      |
|        |           |      | (% of Total |      |      |        |      |      |      |      |      |      |

(continued on next page)
Table 22 (continued)

| Total Count | 110 | 32 | 142 |
|-------------|-----|----|-----|
| % of Total  | 77.5% | 22.5% | 100.0% |

Chi-Square Tests

| Value | Exact Sig. (2-sided) |
|-------|----------------------|
| McNemar’s Test | 0.000^a |

No. of valid cases 142

^a. Binomial distribution used.

Table 23
Logistics performance index * Recovery achieved power (source: Authors, G*Power™ output).

| Exact - Proportions: Inequality, two dependent groups (McNemar) |
|---------------------------------------------------------------|
| Analysis: Post hoc: Compute achieved power                    |
| Input:                                                        |
| Tail(s) = Two                                                 |
| Odds ratio = 0.126                                            |
| α err prob = 0.05                                             |
| Total sample size = 142                                       |
| Prop discordant pairs = 0.5315                                 |
| Output:                                                       |
| Lower critical N = 28.0000000                                  |
| Upper critical N = 48.0000000                                  |
| Power (1-β err prob) = 1.0000000                               |
| Actual α = 0.0286267                                          |
| Proportion p12 = 0.0594751                                    |

Table 24
Transportation investment * Mortality crosstabulation (source: Authors, IBM SPSS™ output).

| Investment | Mortality | Total |
|------------|-----------|-------|
|            | High      | Low   |       |
| High       | 2         | 2     | 4     |
| % of Total | 3.6%      | 3.6%  | 7.1%  |
| Low        | 28        | 24    | 52    |
| % of Total | 50.0%     | 42.9% | 92.9% |
| Total      | 30        | 26    | 56    |
| % of Total | 53.6%     | 46.4% | 100.0%|

Chi-Square Tests

| Value | Exact Sig. (2-sided) |
|-------|----------------------|
| McNemar’s Test | 0.000^a |

No. of valid cases 56

^a. Binomial distribution used.

Table 25
Transportation investment * Mortality achieved power (source: Authors, G*Power™ output).

| Exact - Proportions: Inequality, two dependent groups (McNemar) |
|---------------------------------------------------------------|
| Analysis: Post hoc: Compute achieved power                    |
| Input:                                                        |
| Tail(s) = Two                                                 |
| Odds ratio = 0.072                                            |
| α err prob = 0.05                                             |
| Total sample size = 56                                        |
| Prop discordant pairs = 0.518                                 |
| Output:                                                       |
| Lower critical N = 9.0000000                                  |
| Upper critical N = 21.0000000                                 |
| Power (1-β err prob) = 0.9999840                               |
| Actual α = 0.0427739                                          |
| Proportion p12 = 0.0347910                                    |
Table 26  
Transportation investment * Recovery crosstabulation (source: Authors, IBM SPSS™ output).

|                | Recovery |       |       | Total |
|----------------|----------|-------|-------|-------|
|                | High     | Low   | Total |       |
| Investment     |          |       |       |       |
| High           | 4        | 0     | 4     | 7.1%  |
| % of Total     | 7.1%     | 0.0%  | 7.1%  |       |
| Low            | 36       | 16    | 52    | 28.6% |
| % of Total     | 64.3%    | 28.6% | 92.9% |       |
| Total          | 40       | 16    | 56    | 71.4% |
| % of Total     | 71.4%    | 28.6% | 100.0%|       |

Chi-Square Tests

|               | Value | Exact Sig. (2-sided) |
|----------------|-------|----------------------|
| McNemar’s Test |       | 0.000                |

No. of valid cases 56  
a. Binomial distribution used.

Table 27  
Transportation investment * Recovery achieved power (source: Authors, G*Power™ output).

|                                      | Value     | Exact Sig. (2-sided) |
|--------------------------------------|-----------|----------------------|
| Exact - Proportions: Inequality, two dependent groups (McNemar) |           | 0.000                |
| Analysis: Post hoc: Compute achieved power |           | 0.000                |
| Input: Tail(s) = Two |           | 0.000                |
| Odds ratio = 0.2777160 (for one case instead of zero) |           | 0.000                |
| α err prob = 0.05 |           | 0.000                |
| Total sample size = 56 |           | 0.000                |
| Prop discordant pairs = 0.643 |           | 0.000                |
| Output: Lower critical N = 12.0000000 |           | 0.000                |
| Upper critical N = 25.0000000 |           | 0.000                |
| Power (1-β err prob) = 0.9569164 |           | 0.000                |
| Actual α = 0.0470310 |           | 0.000                |
| Proportion p₁₂ = 0.1397583 |           | 0.000                |
| Proportion p₂₁ = 0.5032417 |           | 0.000                |

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CRediT authorship contribution statement

Peter J. Stavroulakis: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Validation, Visualization, Writing - original draft, Writing - review & editing.

Vasiliki A. Tzora: Formal analysis, Investigation, Methodology, Visualization, Writing - review & editing, Validation.

Elena Riza: Conceptualization, Methodology, Validation. Stratos Papadimitriou: Conceptualization, Methodology, Supervision, Project administration.

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