Perspective

Back from the Future: Mediation and Prediction of Events Uncertainty through Event-Driven Models (EDMs)

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Abstract

The event-driven model (EDM) is an emerging concept in human behavioural research, and understanding how EDMs can promote theory development remains a fundamental quest of predictive science. Traditionally, researchers have heavily depended upon theory confirmation and the inclusion of mediating constructs to clarify uncertainty associated with plausible events (e.g. political, socio-economic, technological, environmental). Though this approach has pushed the field forward, it has also steered mediation research towards largely ignoring the fundamental role of *prediction* as a key for better understanding future events represented by EDMs. Additionally, emerging research using partial least squares structural equation modelling to execute prediction-oriented analysis continues to overlook problematic endogeneity bias and plausible type IV errors due to omitted paths and neglect of indirect effect size estimation in mediation models that embrace the transmittal or segmentation mediation approaches. We aim to introduce prediction as a fundamental option for estimating EDMs and recommend that researchers employ the segmentation mediation approach when estimating EDMs. We further emphasize a novel direct and indirect (v) effect size measure, types of prediction and cases when they are useful. Best practices and practical implications are provided to foster a more useful interpretation of findings.

Keywords

COVID-19, event-driven models, indirect effect size, mediation models, prediction, segmentation mediation, transmittal mediation

Introduction

Event's uncertainty (the likelihood that an event may or may not occur) continues to challenge theory development in human behavioural research (Jurado et al., 2015). This continued struggle with event's uncertainty is problematic for the furthering of science as well as for critical events management. As an example, the Coronavirus Disease 2019 (COVID-19) pandemic is a catastrophic event that has largely impacted human behaviours and organizations across the globe (Kaur & Kaur, 2020; Keni et al., 2020; Sahni et al., 2021), but it was predicted before its final emergence in late 2019 (Smil, 2008; Webster, 2018). Nevertheless, debates evidenced in extant works and the diverse consequences of the COVID-19 pandemic show that developed and emerging economies were not thoroughly prepared for such an event (Hall et al., 2020; Rana, 2021; Zaoui et al., 2021). Thus, better science around events' uncertainty may have been able to provide clearer warning and helped us avoid many of the tragic current circumstances (Bicevska et al., 2016; Douglas, 2009; Hofman et al., 2017).

To resolve this challenge around events' uncertainty science, scholars have debated on relative event-driven models (EDMs) in prediction research (Jurado et al., 2015; Liengaard et al., 2020; Rigdon et al., 2020). In human behavioural sciences, EDMs are yet a relatively new concept and can be defined as theoretically based models that are conceptualized to explain the relationships between a group of events with the intent to aid in the prediction of future events (Baptista et al., 2018; Kesaraju & Ciarallo, 2012; Silver, 2012; Vieira et al., 2000). EDMs are used in cause-and-effect models mirroring political, socio-economic, technological, environmental, legal or other institutional factors (Baptista et al., 2018; Schuberth, 2020; Vieira et al., 2000). A classic and implicit example of the use of EDM-related models to help reduce uncertainty in future events is in the recent work of

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Rahman et al. (2021). In their study, the authors used an EDM to investigate the impact of the COVID-19 pandemic (an event) on management perceptions and tourists' travel risk conceptualized as mediators.

Similar in intent to EDMs, and as a complementary approach to EDMs, mediation models are a traditional method for providing a more precise explanation of causal effects (MacKinnon, 2011). Thus, in an attempt to strengthen the focus on prediction research, several studies advocate the use of mediating constructs to provide broader insights about a given outcome variable (Aguinis et al., 2016; Danks, 2021; MacKinnon et al., 2007; Sarstedt et al., 2020). However, contemporary mediation models often do not explicitly consider prediction (Lapointe-Shaw et al., 2018; Rasoolimanesh et al., 2021). When prediction is the goal, the use and accurate analysis of mediators to examine EDMs is important for several reasons, such as information generation for identifying and predicting the success of intervention events; for identifying mediating constructs that aid in the prediction of events that accumulate over time before their final occurrence; for testing prior theoretical assumptions driving cause and effect to enhance causal–predictive inferences; and others (MacKinnon, 2011). Such information is useful for providing organizational leaders with practical implications to better understand how and what future events will impact business (Danks, 2021; Hair & Sarstedt, 2021; Shmueli, 2010).

In the context of EDMs in human behaviour research, the integration and accurate analysis of mediators is still in its embryonic phase, thus demanding closer attention to ensure more valid practical implications (Agler & De Boeck, 2017; Baptista et al., 2018; Bicevska et al., 2016; Lapointe-Shaw et al., 2018; Tisato & De Paoli, 1995). The science of prediction can aid organizational leaders to develop new and more effective strategies fundamental to dealing with the volatile impacts a disruptive event may have on human behaviour and business operations (Yarkoni & Westfall, 2017). Thus, before an event's occurrence (e.g. disruptive global pandemic), mediation modelling can aid causal–predictive inferences to be made through predictive modelling of EDMs (Morse et al., 2012).

Thus, while EDMs examined via the lens of causal explanations over the years have continued to provide information on when, how and why events occur, they do not inform regarding future events. This task primarily rests on the science of prediction (Hair & Sarstedt, 2021; Sarstedt & Danks, 2021). The science of prediction helps to deepen insights into an uncertain future event's occurrence and offers information on how organizations may better understand what probable event uncertainties are associated with future events, and thus support the preparation for such events' occurrences (Hofman et al., 2017; Kesaraju & Ciarallo, 2012).

Despite numerous efforts of extant research to deepen contemporary insights into how organizations see, understand and prepare for events' uncertainty over the years, little is known of the role prediction plays in EDMs (Danks, 2021; Rigdon et al., 2020). From a theoretical standpoint, predicting events can help enrich hindsight and insight into a defined phenomenon (Suddaby, 2014). While a core focus on theory confirmation helps in falsification, a focus on prediction allows for exploring prescriptive statements that address how and what outcomes might be realized in the future (Jurado et al., 2015; Sarstedt & Danks, 2021; Yarkoni & Westfall, 2017). Nevertheless, studies (Danks, 2021; Douglas, 2009; Hair, 2021; Hofman et al., 2017; Sarstedt & Danks, 2021) lament that the implementation of the science of prediction is yet to be given adequate attention, and extant works employing the statistical methods of prediction within the context of human behaviour research are still sparse.

Prediction can help organizations become more proactive and better prepared in response to emergencies and possible future events' uncertainties (Athey, 2017). Prediction can aid organizations in making more informed decisions and further build organizational resilience against the volatility of constant change (Douglas, 2009). Prediction can help organizations better decipher, collate and coordinate, manage for and project future events' occurrences, thus promoting more meaningful accounts of probable future incidents that were otherwise buried in uncertainty (Hofman et al., 2017; Lane & Maxfield, 2005).

However, despite the relevance of prediction, prior and recent studies continue to overlook its role as a fundamental approach when applying partial least squares structural equation modelling (PLS-SEM) for analysing mediation in the context of EDMs. We aim to fill this gap as part of our contribution. Accordingly, we seek to introduce prediction as a fundamental option for estimating EDMs, specifically through mediation in PLS-SEM analysis. We do this by first addressing the incomplete state of mediation research and how it must shift to better accommodate prediction. Second, we further add to the mediation literature by recommending the use of a novel direct and indirect (v) effects size measure (fundamental for validating prediction models). Third, we introduce specific types of predictions and explain conditions when each type is useful for investigating EDMs. These contributions should help researchers and policymakers to conduct better science around prediction and mediation in EDMs, and perhaps help to predict and even circumvent future tragic events. We hope to provoke a new stream of meaningful and relevant research on the intersection of EDMs, mediation and prediction in PLS modelling (Bicevska et al., 2016; Douglas, 2009; Hofman et al., 2017).

To enrich our literature review, we searched for keywords associated with the distinct concepts of our study across distinct information search engines and those of top journals ranked by the Web of Science or indexed in databases, such as ScienceDirect, Sage, Emerald and others. We examined several keywords including 'event-driven model', 'uncertainty', 'mediation', 'indirect effect

size', 'specific indirect effect', 'prediction', 'mediation' and 'prediction'. In the next section, we extensively examine and challenge the concepts of transmittal and segmentation mediation, and *v* effect sizes in EDMs. We then thoroughly discuss the science of prediction in EDMs, prediction types, their conditions of use and provide our conclusions accordingly.

Transmittal Versus Segmentation Mediation in the Context of Prediction

Recent research continues to explore the concept of *mediation* (Danks, 2021; Sarstedt et al., 2020) and largely embrace the integration of mediating constructs via the transmittal or segmentation mediation approaches (Aguinis et al., 2016; Lapointe-Shaw et al., 2018; Rasoolimanesh et al., 2021). The concept of mediation (M) allows for a part, or whole, transmission of effects from an antecedent (exogenous or 'X') construct to the outcome (endogenous or 'Y') construct. Integrating mediators into a model allows for a more precise analysis of probable events or incidents' occurrences (MacKinnon et al., 2007). By investigating the plausible effect of X on Y through M, or how M complements or competes against the direct effect of X on Y, relative EDMs can be more critically examined, especially with respect to separate times of supposed effects (Lapointe-Shaw et al., 2018).

However, in the context of prediction in PLS-SEM, traditional mediation analysis raises a few problematic methodological concerns. These concerns result from the theoretical and conceptual specifications of constructs and the mismatch of indirect effect size interpretations noted in the segmentation and transmittal mediation approaches (Stone-Romero & Rosopa, 2008; Rungtusanatham et al., 2014). The *transmittal* approach deals with examination, estimation and drawing of inferences on a hypothesis for the effect of M for the relationship between X and Y (Memon et al., 2018). The transmittal approach implies that M is the only intervention construct in a given X–Y relationship and that, despite disparate situations or contexts and times, M must transfer the effect of X–Y (Rungtusanatham et al., 2014). There are certainly conditions where the transmittal mediation approach is applicable, due to strong theoretical support that underpins a linear series of effects like the theories of belief–desire–behaviour or value–attitude–behaviour constructs that reflect that desire or attitude can be analysed as mediators (Rasoolimanesh et al., 2021).

Nevertheless, estimating an EDM via the transmittal mediation approach can impede the possibility for, or degree of, theory advancement when all potential paths like the total effects in a defined EDM are not estimated (Whetten, 1989). In the context of PLS-SEM, researchers employing the transmittal mediation approach consequently limit their specified model's propensity to explore other potential alternative paths observed as one or more direct paths are erroneously ignored (Antonakis, 2017). Despite strong theoretical or empirical support, estimations employing the transmittal mediation approach can lead to questionable findings as a consequence of bias ensuing from endogeneity concerns when applying PLS-SEM (Antonakis et al., 2010; Saxena et al., 2022). Endogeneity concerns may indicate a negligence to theorize or analyse observable potential paths from X to Y (or other intermediary constructs), a disregard of the total effects or a disregard for alternative models in favour of focusing solely on the specific indirect role of M (transmittal mediation approach) (Rasoolimanesh et al., 2021). Rasoolimanesh et al. (2021) provide evidence that several studies focus on indirect effects, while neglecting estimations of their models' direct effects, thereby inflating these indirect effects.

Again, though the transmittal approach may be supported by established theory or prior literature, in an EDM context, it fails to account for the volatile effects of constant change, which, via the passage of time, could have engendered the possibility of X directly predicting Y—though such outcomes are hidden when estimations are solely initiated via the transmittal approach (Schad et al., 2019; Yarkoni & Westfall, 2017). Thus, promoting the continuous implementation of the transmittal approach over time can give birth to misleading policy implications that do not account for or resonate with actual or complete business environment realities influencing organizations (Rungtusanatham et al., 2014).

Conversely, the *segmentation* mediation approach deals with the theorizing of all observable paths as an assessment of the role of M in the X and Y relationship (Rasoolimanesh et al., 2021; Rungtusanatham et al., 2014). The segmentation approach is arguably a more suitable approach for assessing mediation models in the EDM context (Kline, 2015; Lapointe-Shaw et al., 2018; Rasoolimanesh et al., 2021; Tate, 2015) because segmentation allows for (a) the assessment of other observed direct paths in a defined model, (b) provision of broader opportunities for theory development as more information is obtained from distinct paths analysed, (c) an offer of more avenues for challenging or complimenting prior literature and (d) provision of a wider and substantive scope of insights into more meaningful policy implications (Lapointe-Shaw et al., 2018; Tate, 2015). Consistent with prior theoretical or empirical support, the segmentation approach can allow for researchers to further ascertain and account for a probable change in the way M is predicted by X, and how M acts to predict Y, and also influence the X and Y relationship when the direct effect of X and Y is simultaneously estimated in a defined model (Kline, 2015; Rasoolimanesh et al., 2021). In this way, a researcher can inform on whether M plays a competitive or complementary role in a specified X and Y relationship. This is representative

of conditions where the effect of X is negative or reduced by M (competitive), which in turn causes an increase or positive effect on Y (complementary), and vice versa (Nitzl et al., 2016).

Nevertheless, several extant works continue to inappropriately apply segmentation mediation due to a lack of theoretical or empirical justification for using indirect effects and a disregard of interpretation of the indirect effect size results (Rasoolimanesh et al., 2021; Kline, 2015; Lachowicz et al., 2018). Studies contend that researchers ought to give closer consideration to the reporting of indirect effect sizes, as this facilitates deeper, more meaningful and more robust policy implications (Kline, 2015; Lachowicz et al., 2018). Researchers may want to note that when prediction is the goal in EDMs, overlooking the estimation and reporting of the indirect effect size in a study can lead to inaccurate conclusions of findings (Agler & De Boeck, 2017; Hair, 2021). Consequently, although the results obtained may be statistically significant, the information quality and content of the conclusions deduced from the findings remain incomplete, as the magnitude of the effect of results from indirect effect estimates is excluded, due to sole reliance on *p*-values (Kline, 2015; Tate, 2015). Therefore, such findings and subsequent conclusions are not only limited, misleading and inherently flawed, but they also signal a plausible bias associated with type IV error (Betz & Gabriel, 1978; Ottenbacher, 1992).

A type IV error occurs when there is an incorrect interpretation of a null hypothesis that is also correctly rejected—such as in the case of receiving a correct diagnosis of an ailment by a physician, followed by a prescription of an incorrect or incomplete medication (Umesh et al., 1996). Similarly, while significant results inferred from *p*-values aid to obtain constructive evidence of the existence and role of future events, and upon which conclusions can be deduced, excluding information about the indirect effect sizes of such future events would result in a prescription of incomplete and inadvertently misleading policy implications (Kline, 2015; Sullivan & Feinn, 2012; Tate, 2015). Therefore, to do better science around prediction and mediation in EDMs, and to offer more meaningful practical implications, it is important to not only rely solely on *p*-values but also complement them with results of indirect effect sizes. This is relevant for understanding the possible size of an event's impact predicted by an EDM. While these insights have certainly been identified in prior literature, the practice is not being followed in EDM research, and therefore merits renewed emphasis.

Estimating Direct and Indirect Effect Sizes in Event-driven Models

Having a better understanding and reporting of the effect sizes of events can help provide useful information as to the degree and weight of impact that a predicted event (e.g. the COVID-19 pandemic—Alon, 2020) might likely have on human behaviour and business operations. Yet, this practise is not common (Ferguson, 2009; Lachowicz et al., 2018). Recent debates promote the shift away from relying solely on null hypothesis significance tests and *p*-values as the primary source of testing hypotheses (Ferguson, 2009; Sullivan & Feinn, 2012). Agler and De Boeck (2017), Tomczak and Tomczak (2014) and Lachowicz et al. (2018) advocate that the use of effect sizes is mandatory and acts as a complementary support for hypothesis testing. We argue that effect sizes (direct and indirect) are especially useful in EDMs (Lapointe-Shaw et al., 2018). By overlooking the estimation and proper reporting of effect sizes in EDMs, postulated findings that ought to capture substantive meanings associated with the strength of relationships between constructs are ignored (Tomczak & Tomczak, 2014). This can also hamper comparisons of results from alternative sources of evidence investigating a phenomenon and inadvertently limit meaningful findings that could have otherwise advanced contemporary understandings of a broader phenomenon (Shmueli et al., 2019). Consequently, findings could provoke inference of wrong conclusions, drawn as solutions to correctly specified postulations (Ottenbacher, 1992), leading to a type IV error (Betz & Gabriel, 1978; Rai, 2017; Umesh et al., 1996).

As concerns about the need to remedy the discrepancies between effect sizes and confidence intervals linger, it is worth understanding that for EDMs, confidence intervals and *v* effect sizes remain an appropriate and established standard for estimating mediating effects (Agler & De Boeck, 2017; Lapointe-Shaw et al., 2018). However, in some EDMs, the *v* effects may seem too small to be worth considering for practical implications and decisions (Wen & Fan, 2015). While mediation may be established via confidence intervals in a given EDM, with a resulting *v* effect that is negligible, it is important to note that even a smaller *v* effect size does not necessarily rule out the existence of an already established mediation (Sullivan & Feinn, 2012; Tomczak & Tomczak, 2014). Regardless of the effect size, competing *v* effects in a given EDM may rule out each other and, thus, diminish the value of *v* effects in respective estimated paths (Agler & De Boeck, 2017; Lachowicz, Preacher, & Kelley, 2018). In EDMs, confidence intervals are not particularly superior to effect sizes, and neither are effect sizes superior to confidence intervals—both play complementary roles to further enhance our understanding of predicted outcomes (Hofman et al., 2017). Nonetheless, confidence intervals produced through bootstrapping are of importance to test hypothesized processes for establishing that a certain event may occur with respect to a generally acceptable degree of assurance (Wen & Fan, 2015; Warner, 2013). Moreover, the *v* effect size measure helps to provide information about the degree of impact that an event that is likely to occur may have

(Preacher & Kelley, 2011). Therefore, confidence intervals and *v* effect size complement each other by indicating the size of a specific indirect effect through effect size, as well as the uncertainty around that effect through confidence intervals (Agler & De Boeck, 2017).

Values of indirect effects are often small, and meaningful *v* effect sizes may require a sample size of at least 500 in cases of unstable mediated paths (Ferguson, 2009; MacKinnon et al., 2007). Similarly, a small indirect effect value might mean that the *v* effect size may likely be small (Lachowicz et al., 2018). However, the works of Agler and De Boeck (2017) and Lowry and Gaskin (2014) further relate that though an effect size is extremely small (and probably negligible), it can be meaningful to support the signal of a process, and information obtained in this case could serve as a substantive contribution for supporting future predictions of a specific event (Hofman et al., 2017; Liengaard et al., 2020). Likewise, to account for *v* effect sizes, Lachowicz et al. (2018) argue that researchers should *square* the specific standardized *v* effects,[1] and Ogbeibu et al. (2021) expounded on the estimation of *v* effect sizes and proposed the halving of Cohen's (1988) effect size measure to allow for a more meaningful interpretation of naturally small *v* effect sizes. Therefore, Cohen's (1988) effect size measure of 0.02 (small), 0.15 (medium) and 0.35 (large) would be *0.01* (small), *0.075* (medium) and *0.175* (large).

We further recommend that in a situation where an estimated EDM has objective rather than perceptual measures, this new *v* effect size criteria could also be used for estimating *direct effect sizes* for EDMs (Sullivan & Feinn, 2012). We recommend this approach because objective measures consistently share less variance than perceptual measures, which are known to have inflated shared variance due to myriad external influences (Podsakoff et al., 2012). Consequently, effect sizes are artificially high for perceptual measures and artificially low for objective measures. Moreover, with regard to the passage of time that may account for possibly multiple events in EDMs (signalling respective direct paths or the segmentation mediation approach), the indirect effect size measure proposed by Ogbeibu et al. (2021) mirrors a more approachable and appropriate threshold with regard to comparing the strength of occurrences of outcome probabilities from across distinct interventions. Nevertheless, taking into consideration the diversity of a given population of a given study, the choice of effect size measure should be informed by context and nature of investigation (Sullivan & Feinn, 2012).

The Science of Prediction in Event-driven Models

Extant literature advocates the need for scholars to take into consideration the underlying time factor endemic within EDMs (Stone-Romero & Rosopa, 2008). The work of Aguinis et al. (2016) reflects that the passage of time inherently exists in causal paths of EDMs. Stone-Romero and Rosopa (2008) also argue that the influence of X on Y through M is not instantaneous, as it might take several weeks or months for the effects of X to influence M and, subsequently, Y. The passage of time is even more pronounced in models with multiple serial mediators (Lapointe-Shaw et al., 2018). Consequently, there is a high level of uncertainty of plausible events that may have occurred, or are occurring, during the period of research investigation, that could impact the influence of X on Y through M (MacKinnon et al., 2007). Therefore, each path from X to M and M to Y, respectively, is laced with uncertain intervention events that can attempt to confound the inference of causality in a given EDM considering the already existing inherent time lag (Mathieu & Taylor, 2006).

This uncertainty is a possibility largely because in EDMs, the postulated path from X to M may change at the occurrence of specific events, thus inherently altering the path from M to Y. Likewise, while investigating a hypothesized path from X to Y, the occurrence of a specific event can also alter the anticipated outcome on Y (MacKinnon et al., 2007). Thus, when an event is not predicted (given an event's inherent role of interference as a probable mediator) during research investigations, the final policy implications obtained from such studies can be misleading as such policy implications are susceptible to the bias of extricating timely factors from an organization's actual reality (Danks, 2021; Shmueli, 2010). Events that organizations have little or no control over, and that can influence business decisions and operations, are often captured as factors within organizations' external environment (Grant et al., 2020). There is, therefore, a need to employ the science of prediction to more closely capture relevant events (in and across distinct times) that can help to best describe a possible reality and provide more reliable information for more meaningful policy implications (Silver, 2012). In EDMs, prediction analysis can, therefore, aid to explain a gradual, radical or transformative change in the state of X–M, M–Y and the specific indirect role of M at a given point in time (Agler & De Boeck, 2017; MacKinnon et al., 2007). The science of prediction creates room for causal–predictive analysis, which is a valuable system for evaluating theoretically specified linkages between events, and reduces the degree of uncertainty associated with events' occurrences (Shmueli et al., 2019).

Stone-Romero and Rosopa (2008) argued that the use of theories for supporting empirical investigations is imperative and provides a valuable condition for predicting a phenomenon. Prediction is, thus, a recommended choice when estimating EDMs because, by predicting, one can understand and better explain events' uncertainty with more practical accuracy (Shmueli, 2010). Prediction helps

amplify knowledge in the causal explanation of events in ways that reinforce the contradicting and verifiability of theoretical assumptions supporting a given phenomenon (Hofman et al., 2017). In EDMs, the science of prediction helps to foster practical relevance, theory falsification and has been further advocated to be the primary criterion for ascertaining the accuracy and relevance of disparate events (Hofman et al., 2017; Shmueli, 2010).

The quest to predict event uncertainty is statistically complex, though it remains a necessary task for behavioural scientists (Lane & Maxfield, 2005; Rigdon et al., 2020). Yet the science of prediction that allows for ascertaining the degree to which an EDM exhibits high, medium or weak predictive power lacks sufficient consideration in behavioural science research (Shmueli et al., 2019). This paucity in the prediction literature limits understanding and our ability to closely capture plausible realities embedded in uncertain future events (Jurado et al., 2015; Hofman et al., 2017). Likewise, by ignoring the need to assess the predictive power of EDMs, useful information about out-of-sample data is inadvertently obscured (Shmueli et al., 2016). Recent advances in prediction science imply a need to assess an EDM's predictive power, as this is important to provide meaningful information about the degree to which a specified EDM can predict a defined phenomenon (Hair, 2021; Shmueli et al., 2019). Results from a predictive power analysis validate an EDM's prediction strength, thus increasing the validity of causal theoretical assertions (Sharma et al., 2018).

While information about an EDM's predictive power indicates an EDM's accuracy when predicting the outcome value of new cases, Rasoolimanesh and Ali (2018) lament that there is a need to have clear guidelines for estimating predictive power. Therefore, to estimate and account for predictive power, we recommend comparing respective indicator values of the root mean squared error (RMSE) or mean absolute error (MAE) for the PLS-SEM analysis against those of the linear regression model's (LM) respective indicator values. Lower prediction errors of RMSE (or MAE) *for all* indicators of the PLS-SEM analysis, when compared to the LM's respective indicators, suggest *high* predictive power. Likewise, a case of lower prediction errors of RMSE (or MAE) *for the majority* of indicators of the PLS-SEM analysis, when compared to corresponding LM's indicators, suggests *medium* predictive power. Following the same logic, the *lesser* number of indicators suggests *a low* predictive power and a case where *none* of the PLS-SEM RMSE (or MAE) indicators exhibit lower prediction errors when compared to the LM values suggests a lack of predictive power (Shmueli et al., 2019). These guidelines are especially relevant for interpreting the degree to which a specified EDM demonstrates the ability to predict a phenomenon with realistic precision. Consequently, such metrics can provide organizational leaders and policymakers with more confidence regarding the degree of certainty that an event may occur.

Types of Predictions in the Event-driven Models Context and Cases When They are Useful

Cross-sectional Prediction

This kind of prediction closely mirrors the cross-sectional study design and model. Including a mediation construct in a cross-sectional model would imply an EDM where a prospective or longitudinal prediction (see subsequent discussions) would be more appropriate (Spector, 2019). In the human behavioural sciences, cross-sectional prediction has historically been the most popular among researchers and practitioners (Sharma et al., 2018; Spector, 2019; Spector & Pindek, 2016). Cross-sectional prediction deals with the observation and single-point-in-time analysis of an event in order to predict the prevalence of such event outcomes (Wang & Cheng, 2020). Cross-sectional prediction is appropriate as a beginning point for accessing and investigating sparse events where simple models are initially developed due to limited information surrounding a defined phenomenon. The aim generally would be to gravitate from simple designs towards more complex ones as increased availability of information emerges about a given event. Cross-sectional prediction is especially useful in cases where there is no certainty that an event X influences an event Y. Congruently, such a case is usually one where there is established uncertainty—often found in new fields of research with limited information. Often, for events eclipsed by high levels of uncertainties, it can be quite challenging to account for the time required for event X to lead to, or influence, event Y. Consequently, deploying EDM (which is grounded in segmentation mediation) under such conditions may provoke unrealistic and questionable findings due to high uncertainty limiting causal confidence (Wang & Cheng, 2020).

Prospective Prediction

In prospective prediction, it is assumed that there is an already established theory and available information, which may not only be sufficient to support the prediction of an event but can also help inform regarding plausible time variations of event occurrences (Lapointe-Shaw et al., 2018; Sanbonmatsu & Johnston, 2019). Consequently, prospective prediction is consistent and built upon a pool of established cross-sectionally predicted findings. Insights that aid event outcome expectations can thus be obtained, and probable time separations between distinct but correlated events can be observed. Prospective prediction uses the segmentation mediation approach. Discrepancies in inconclusive evidence about a defined phenomenon across diverse contextual and domain factors provoke the necessity and importance for prospective prediction (Douglas, 2009). EDMs are usually more aligned with prospective prediction as their advocated specifications allow for temporal separations or time lags

between disparate yet correlated events (MacKinnon et al., 2007). An example can be observed in a case where data for all the exogenous constructs representing distinct events are obtained at one point in time, and data are also collected for the endogenous constructs at a separate point in time. In EDMs, cases of serial mediators are grounds for more temporal separations to be considered between respective exogenous and endogenous constructs (Jordan & Troth, 2020; Spector, 2019; Stone-Romero & Rosopa, 2008). However, it is important to note that in serial mediation, one is not just multiplying a decimal by another decimal, but such estimation is done for as many segments evidenced in the model, and, each time such estimation is executed, the indirect effect shrinks.

Longitudinal Prediction

Longitudinal prediction is relevant when all events captured as constructs in a specified EDM are examined at the same point in time and then repeated multiple times across a defined period (Aguinis et al., 2016; Spector & Pindek, 2016; Yarkoni & Westfall, 2017). Longitudinal prediction is quite useful when it is possible to determine the correlation between events. When underpinned by established theoretical assumptions along with domain-relevant information, longitudinal prediction becomes more useful for predicting intervention effects and for cases where multiple events are likely to occur as outcomes (Douglas, 2009).

To account for a specific outcome in situations where events (discrete events, e.g. occurrences of the COVID-19 variants—Kanupriya, 2020) are expected to occur between waves of a defined investigation, a longitudinal prediction would be a more suitable approach (Hofman et al., 2017; Shmueli, 2010; Spector, 2019). Similar to prospective prediction, longitudinal prediction is also recommended when the time gap between events X–Y, X–M and M–Y is known. This is such that the time delay required for event X to influence event Y, or for event X to influence event M and for event M to influence event Y are directly observable and known (Jordan & Troth, 2020; Spector, 2019; Stone-Romero & Rosopa, 2008). In light of a plethora of available information about an EDM, or when a phenomenon is well supported by established theoretical assumptions, the use of the prospective or longitudinal predictions is to be further supported by control variables as a strategy to rule out alternative explanations (Atinc et al., 2012; Bernerth & Aguinis, 2016; Spector, 2019).

Conclusion

Deploying the science of prediction through mediation in EDMs is a necessity, for better understanding and explaining events eclipsed by uncertainty, as well as predicting events with reasonable accuracy. Accordingly, we have examined contemporary prediction and mediation issues in the EDM context, and we offer insights that capture prediction as a fundamental option for estimating EDMs, specifically through mediation in PLS-SEM analysis—which has been previously overlooked. We have also advanced the mediation literature by recommending the use of a novel *v* effect size measure, introducing prediction types and explaining their conditions of usefulness in EDM investigations. These contributions are relevant for supporting researchers and practitioners in their effort to predict future events.

Prediction is a useful tool for not only generating valid arguments that infer causality but also for producing reliable results that are causal–predictive. Prediction is the most recommended PLS-SEM tool for estimating EDMs. To avoid producing biased results from an EDM, it is important to carefully consider a defined EDM's key aims, scope and supporting theory and match them against a relative type of prediction—*cross-sectional*, *prospective* or *longitudinal*. The use of theory to drive and explain linkages of distinct events is usually the first step when developing an EDM.

EDMs ought to be specified and estimated via the segmentation mediation approach to allow for the prediction of outcomes along with sequential occurrences of distinct events. Consistent with reasons previously noted, applying the segmentation mediation approach in EDMs is crucial as it helps to support considerations for time delays across a defined period. While we strongly recommend that EDMs and mediation investigations adopt the segmentation mediation approach, we discourage the use of the transmittal mediation approach, especially in EDMs. We also recommend effect size measures to support our emphasis on the need for both direct and *v* effect sizes to be reported in EDMs, as this is especially important to broaden the understanding of a particular phenomenon and further deepen insights into the size of the impact that a predicted event may have.

Implications

When prediction is the goal, the use and accurate analysis of mediators to examine EDMs can aid organizational leaders with a practical guide to better understand how and what future events may impact business operations and objectives. By embracing the science of prediction, organizational leaders might develop innovative and more effective strategies fundamental to addressing volatile effects a disruptive event may have on their business practices. Moreover, the three types of predictions can help future research studies understand and apply appropriate prediction techniques that better capture their theoretical model and undergird more valid results and reliable implications for practice. It is also important for future EDM-grounded research to discontinue the use of the transmittal approach, as it can promote misleading policy implications that do not align with actual business

environment realities impacting organizations. Conversely, the segmentation mediation approach should be adopted especially in cases where EDMs are examined. By applying the segmentation mediation approach, future investigations might tap into more robust and valid inferences relevant for advancing policy, theoretical implications and practical implications. Future research should be careful to not overlook the estimating and reporting of *v* effect sizes and should consider their respective ability to broadly inform on the weight and degree of impact an event may have on business activities and human behaviour.

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Note

1. See video demonstration links: https://youtu.be/kyPUHCMjPyg and https://www.youtube.com/watch?v=e-594jcFVxY&t=29s

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