Please, hurry up! Leveraging narratives to speed up the mobilization of resources for entrepreneurial ventures

David Johnson¹

Durham University The Waterside Building Riverside Place Durham, DH1 1SL UK ORCiD: 0000-0002-5378-0982

Mark Geiger

Duquesne University 600 Forbes Avenue Pittsburgh, PA 15282 USA <u>geigerm1@duq.edu</u> ORCiD: 0000-0001-9856-3597

Peter T. Gianiodis

Duquesne University 600 Forbes Avenue Pittsburgh, PA 15282 USA <u>gianiodisp@duq.edu</u> ORCiD: <u>0000-0002-5714-5775</u>

Adam J. Bock University of Wisconsin-Madison 975 University Avenue Madison, WI 53590 USA bock2@wisc.edu

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¹ Corresponding author.

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David Johnson (<u>david.johnson@durham.ac.uk</u>) is an Associate Professor in Entrepreneurship at Durham University Business School, Durham University. His research is centered on academic entrepreneurship, life science commercialization, technology transfer, and university-industry engagement activities. He earned his PhD from the University of Edinburgh.

Mark Geiger (geigerm1@duq.edu) holds the Warco Faculty Fellowship in Entrepreneurship and is an Associate Professor at the Palumbo–Donahue School of Business at Duquesne University. His research interests include meta-analysis, quantitative methods, and individual differences in entrepreneurship and organizations. He earned his PhD from the University of Kansas.

Peter T. Gianiodis (gianiodisp@duq.edu) holds the Merle E. Gilliand Professorship in Entrepreneurial Finance at the Palumbo–Donahue School of Business at Duquesne University. His research interests are at the intersection of entrepreneurship, technology management, and strategy. He researches market entrance of new and growing ventures, as well as the university-based technology commercialization. He earned his PhD from the University of Georgia.

Adam J. Bock (<u>bock2@wisc.edu</u>) is Adjunct Faculty at the University of Wisconsin-Madison and an Executive-in-Residence at the University of Minnesota Discovery Launchpad. His research interests include business models, angel financing, and entrepreneurial narratives. He earned his PhD from Imperial College London.

ABSTRACT

Narratives are important facilitators of resource mobilization. Specifically, entrepreneurs and ventures utilize narratives to persuade stakeholders to part with resources to support innovative activities and entrepreneurial action. We investigate the narrative discourse of university-industry contract research proposals to understand how language determines the speed of contract research acceptance/rejection (i.e., speed to decision) and the mobilization of non-financial capital resources. Ventures that can increase decision-making speed can gain access to valuable resources quicker, which supports their orchestration. Utilizing Linguistic Inquiry and Word Count (LIWC), we explore the narrative content of 3,422 contract research proposals. Findings show a positive association of entrepreneurial-oriented language and specific cognitive-oriented language with decision-making speed, which in turn shows a positive association with contract research proposal acceptance. Our findings have important implications for theory, practice, and policy.

Keywords: Narratives; Linguistic Properties; Speed to Decision; Resource Mobilization; Entrepreneurial Ventures; University-Industry Engagement

INTRODUCTION

Entrepreneurial ventures face resource constraints, especially during periods of innovative activity, including opportunity development and value creation (Baker & Nelson, 2005; Carnes, Hitt, Sirmon, & Chirico, & Huh, 2022). In these circumstances, the speed at which resources are mobilized becomes critical to enable ventures to exploit viable opportunities, innovate, and remain competitive (Clough, Fang, Vissa, & Wu, 2019; Thornton, Henneberg, Leischnig, & Naudé, 2019; Zahra, 2021). Narratives are important mechanisms to support entrepreneurs and ventures in mobilizing resources, which is the basis of cultural entrepreneurship (Lounsbury & Glynn, 2001; Manning & Bajarano, 2017; Martens, Jennings, & Jennings, 2007). Unfortunately, research exploring the use of narratives to build entrepreneurial capital pay less attention to the role of time, prompting the need to investigate the time-resource mobilization relationship (Thornton et al., 2019; Zahra, 2021). Specifically, how the narrative is constructed, such as the specific language utilized and how this influences decision-making speed and the time to successful resource mobilization, requires further investigation (dos Santos Felipe, Mendes-Da-Silva, Cerqueira Leal, & Santos, 2022).

Whilst acquiring financial capital is a prerequisite for ventures, non-financial capital resource acquisition, such as human capital, is equally important (Coad, Nielsen, & Timmermans, 2017; Hertel, Binder, & Fauchart, 2021). However, research overlooks the use of language to facilitate the mobilization of non-financial capital resources. At the same time, prior research largely focuses on online crowdfunding pitches (see Short, Ketchen, McKenny, Allison, & Ireland, 2017, for a review), as well as firms' initial public offering (IPO) prospectuses (Blevins, Ingram, Tsang, & Peng, 2019; Wales & Mousa, 2016), as a narrative mechanism facilitating access to resources. Unfortunately, these approaches do not appropriately recognize other narrative mechanisms (e.g., contract research proposals) that can also facilitate access to resources.

Consequently, we know little about i) how language influences speed to resource mobilization; ii) the mobilization of non-financial capital resources; and iii) alternative narrative mechanisms that facilitate access to these resources.

In this study, we examine a novel and alternative narrative mechanism – universityindustry contract research proposals. We ask: *how does the language utilized within universityindustry contract research proposals affect the speed to decision and proposal outcome?* Specifically, utilizing Linguistic Inquiry and Word Count (LIWC) software (Pennebaker, Francis, & Booth, 2001), we explore the narrative content of 3,422 industry-initiated contract research proposals submitted to Scottish Universities to understand how the specific language utilized within contract research proposals determines the speed of contract research acceptance or rejection (i.e., the speed to decision) and the mobilization of non-financial capital resources by industry partners.

Despite the importance of academic-industry engagement as an economic lever (Casper & West, 2024; Fini, Rasmussen, Siegel, & Wiklund, 2018; Johnson, Gianiodis, Harrison, & Bock, 2023; Meek & Gianiodis, 2023), little research exists to understand how the discourse embedded in contract research proposals influences ventures' access to resources (Vaara, Sonenshein, & Boje, 2016). Contract research operates as a two-sided dynamic; ventures (i.e., resource seekers) attempt to mobilize non-financial capital resources, namely specialized academic knowledge and/or access to specialized university facilities/equipment, from academic scientists (i.e., resource providers) (Wirsich, Kock, Strumann, & Schlutz, 2016). To secure these services from academic scientists, ventures must develop formal processes; for example, the narrative in the contract research proposal contains specific discourse to persuade academic scientists to engage with the venture. In this sense, the proposal is dyadic; it is a conduit to inter-organizational boundary

spanning activities for both parties. Accordingly, engagement depends on an individual academic's motivation and decision to contract with the venture (Balven, Fenters, Siegel, & Waldman, 2018; Hmieleski & Powell, 2018), and we argue that the narratives in the proposal compel academics' decisions in meaningful ways. Of particular importance is the speed at which a decision is made by an academic to contract with the venture, which we define as *speed to decision*.

By investigating the relationship between language, speed to decision, and resource mobilization, we contribute to cultural entrepreneurship scholarship (Jancenelle, Javalgi, & Cavusgil, 2019; Lounsbury & Glynn, 2001; Martens et al., 2007) and university-industry engagement (Perkmann et al., 2013; Perkmann, Salandra, Tartari, McKelvey, & Hughes, 2021). First, we build upon the narrative perspective on resource mobilization (Lounsbury & Glynn, 2001; Manning & Bejarano, 2017; Martens et al., 2007; Moss, Renko, Block, & Meyskens, 2018) by addressing the shortcomings of existing resource mobilization literature that ignores the role of time (see Zahra, 2021, for a review). Specifically, we show how the use of entrepreneurial-oriented language (EOL) and cognitive-oriented language (COL) influences speed to decision and, subsequently, resource mobilization. Second, we address concerns related to the disproportionate focus on the mobilization of financial capital resources (Clough et al., 2019; Hertel et al., 2021) by describing how specific language can be used to mobilize non-financial capital resources, including access to human capital and specialized facilities. In practice, non-financial capital resources are critical in driving science commercialization activities at the university-industry boundary (Clayton, Feldman, & Lowe, 2018; Hmieleski & Powell, 2018). Third, recognizing the predominant focus on online crowdfunding pitches (Short et al., 2017), we enrich prior studies by investigating other forms of narratives. Specifically, we seek to determine whether findings from prior crowdfunding studies generalize to other contexts such as university-industry contracting

(De Wit-de-Vries, Dolfsma, Van der Windt, & Gerkema, 2019; Perkmann, McKelvey, & Phillips, 2019). In response, we show how specific language used within contract research proposals is related to speed to decision and the mobilization of non-financial capital resources. In doing so, we make a fourth contribution to university-industry engagement scholarship and policy (Meek & Gianiodis, 2023; Mbitse, Salomo, & zu Knyphausen, 2024; Perkmann et al., 2013; 2021) by being the first to consider how language within contract research proposals can prompt entrepreneurial action by faculty scientists, and thus influence university-industry engagement outcomes.

LITERATURE REVIEW

Resource Mobilization, Narratives, and Speed to Decision

Entrepreneurial ventures have inherent resource constraints. Given their limited histories, lack of legitimacy, and limited financial capital, they must become creative in acquiring and mobilizing resources (Baker & Nelson, 2005; Stinchcombe, 1965). Access to and the orchestration of resources is a critical condition that determines how ventures innovate and progress opportunities along the entrepreneurial process (Carnes et al., 2022; Schoonhoven, Eisenhardt, & Lyman, 1990; Qin, Wright, & Gao, 2017). The mobilization of resources involves "the processes by which entrepreneurs assemble the resources to execute an opportunity" (Clough, 2019: 240).

Narratives are shown to be important mechanisms for organizations to accomplish entrepreneurial activities (Wolfe & Shepherd, 2015) and sustain organizational innovation (Bartel & Garud, 2009). During venturing, a well-crafted narrative that aligns with stakeholder expectations can enable resource acquisition and deployment (Lounsbury & Glynn, 2001; Martens et al., 2007). Central to this research is how entrepreneurs pursue critical resources through purposeful narratives targeting influential stakeholders (Kim, Buffart, & Croidieu, 2016; Manning & Bejarano, 2017). The specific language utilized by entrepreneurs and ventures within their narratives determines whether they are successful in accessing financial capital resources (Anglin,

Short, Drover, Stevenson, McKenny, & Allison, 2018; Moss et al., 2018; Parhankangas & Renko, 2017). For example, research demonstrates how function and psychological process words influence financial resource providers (Kim et al., 2016), emotional and cognitive language influences funding outcomes (Moradi & Badrinarayanan, 2021), and entrepreneurial-oriented language (EOL) influences funding success (Calic & Schevchenko, 2020).

Unfortunately, we know little about the speed at which resources are mobilized (Zahra, 2021). An important stream of narrative research that can address this gap focuses on the link between EOL and individual and organizational behavioral responses and action (Moss, Neubaum, & Meyskens, 2015; Titus, Parker, & Covin, 2020; Wolfe & Shepherd, 2015). For instance, studies show that narratives with EOL improve funding outcomes for micro-enterprises (Moss et al., 2015), serve as a strategic posture for corporate venturing (Titus et al., 2020), and influence performance following a loss (Wolfe & Shepherd, 2015). This research widely recognizes the relationship between EOL, decision-making, and the mobilization of resources (Calic & Schevchenko, 2020; Lumpkin & Dees, 1996; McKenny, Short, Ketchen Jr., Payne, & Moss, 2018; Moss et al., 2015), making it an appropriate topic for our investigation. While scholars demonstrate how ventures' EOL can be captured in written text (Calic & Schevchenko, 2020; McKenny, Aguinis, Short, & Anglin, 2016; Short, Broberg, Cogliser, & Brigham, 2010), our understanding of how EOL influences speed to decision remains limited.

Another important stream of narrative research focuses attention on entrepreneurial cognition, reflecting the knowledge structures that individuals use to assess, judge, decide, and act upon commercialization (Johnson & Bock, 2017; Sassetti, Marzi, Cavaliere, & Ciappei, 2018). Whilst this literature focuses on how individual entrepreneurs construct their cognitive discourse (e.g., Byrne & Shepherd, 2015), studies also explore how individuals interpret and act upon

cognitive discourse (Peng, Cui, Bao, & Liu, 2021). Again, the relationship between COL, decisionmaking by resource providers, and the mobilization of resources has been recognized, providing a theoretical foundation for our investigation. For instance, research shows how COL in a firm's initial public offering (IPO) prospectus leads to more favorable pricing from investors (Wales & Mousa, 2016) and that COL utilized in crowdfunding campaigns is linked to resource acquisition (Kim et al., 2016; Moradi & Badrinarayanan, 2021; Parhankangas & Renko, 2017). However, we know very little about how COL influences speed to decision.

University-Industry Engagement

We investigate university-industry contract research, which describes the engagement between external organizations and university academic scientists, whereby the academic scientist performs contract research. Typically, the industrial partner has specific objectives, notably scientific or technical problems, which it would like the university academic scientist to help resolve (Spithoven, Teirlinck, & Ysebaert, 2020). Industry-initiated contract research projects have a pre-determined scope or specification and are unique to each venture. These project scopes are distributed to academic scientists with appropriate skills and/or research domains aligning to the project scope.

Entrepreneurial ventures are often resource constrained, which makes engaging with universities an attractive, cost-effective, and risk-sharing proposition (Alexandre, Costa, Faria, & Portela, 2022). University-industry engagement can drive venture innovation (Anckaert & Peeters, 2023), especially where the industrial partner is an entrepreneurial venture (Dornbusch & Neuhäuser, 2015). Contract research is an important mechanism for accessing specialized human capital resources (Hmieleski & Powell, 2018; Jones & Corral de Zubielqui, 2017) and university facilities/equipment – e.g., laboratories, specialist equipment, etc. (Clayton et al., 2018). Such engagement activities promote the emergence and development of university-centered

entrepreneurial ecosystems (Casper & West, 2024; Johnson et al., 2023; Mbitse et al., 2024).

There are several factors that motivate ventures to engage with universities. First, universities have access to specialized academic knowledge and facilities/equipment (i.e., non-financial capital resources), which can enhance ventures' knowledge base and progress novel opportunities (Sjöö & Hellström, 2021). This is an advantageous strategy for ventures because it is a more cost-effective way than developing their opportunities in-house (Ankrah, Burgess, Grimshaw, & Shaw, 2013). Second, ventures are motivated to engage with academics to access solutions to technological problems, which can facilitate prototype and product/service development (Bodas Freitas & Verspagen, 2017; Broström, 2010). Consequently, this engagement can support ventures with their innovative activities (Bellucci & Pennacchino, 2016). Third, ventures may also collaborate with universities in response to governmental initiatives, policies, or incentives (Ankrah et al, 2013). For example, government subsidies for university-industry collaborations can drive knowledge spillovers, innovation, and profits (Kleine, Heite, & Huber, 2022).

Whilst it is evident that industry partners benefit from engagement with universities, engagement requires academic scientists' participation to create value (Ankrah & Al-Tabba, 2015). University-industry engagement is a two-sided relationship in which the academic scientist/university, notwithstanding the specific language utilized within the contract research proposal, must be incentivized to provide access to their resources (De Wit-de Vries et al., 2019). This is especially important given role identity conflicts that prioritize research and teaching over contract research/commercial activities (Meek & Gianiodis, 2023).

THEORETICAL CONTEXT

For entrepreneurial ventures, time is a scarce resource that can mean the difference between success and failure (Markman, Siegel, & Wright, 2008). Since opportunities are time bound

(Kirzner, 1973), ventures that can reduce the time between opportunity identification and commercialization are in a better position to exploit the opportunity and create and capture its value (Qin et al., 2017). Complementing this view, resource providers also act entrepreneurially, choosing from a range of opportunities to allocate scarce resources. Accordingly, they too have incentives to act quickly (Blevins et al., 2019). While many innovations have defined gestation periods, there are key decision points where speed can accelerate progress for both resource seekers and resource providers.

Given the importance of EOL and COL to financial resource mobilization (Calic & Schevchenko, 2020; Moradi & Badrinarayanan, 2021; Parhankangas & Renko, 2017; Sahaym, Datta, & Brooks, 2021), understanding the relationship between language and speed to decision, and how this influences the mobilization of non-financial capital resources, is timely. In the following sections, we develop three hypotheses to provide an understanding of the mechanisms connecting the EOL and COL of contract research proposal narratives to the speed of resource providers decision on a proposal and proposal outcome. Figure 1 provides a visual representation of our theoretical model.

Insert Figure 1 about here

Hypothesis Development

Our central proposition is that a venture's degree of EOL and COL in a contract research proposal influences the decision speed of resource providers. Our framework is rooted in decision-making literature (Bakker & Shepherd, 2017) and is based on processes related to signaling theory (Connelly, Certo, Ireland, & Reutzel, 2011; Connelly, Certo, Reutzel, DesJardine, & Zhou, 2024; Spence, 1973) and decision-making heuristics (Artinger, Petersen, Gigerenzer, & Weibler, 2015).

We integrate these theoretical underpinnings to provide insights into decision speed as a mechanism through which signals influence decision outcomes and ultimately access to external resources for entrepreneurial ventures.

Signaling theory and decision-making heuristics support our central proposition in a couple of ways. First, signaling theory helps explain individual and firm behavior when information asymmetries exist between insiders (entrepreneurial ventures) and outsiders (resource providers) (Connelly et al., 2011). It suggests that insiders provide information to outsiders to communicate qualities of the signaler to the receiver (Spence, 1973). This information can include signals about a person or an organization (Connelly et al., 2011). In the context of our study, entrepreneurial ventures are replete with information asymmetries in which entrepreneurs (signalers) possess information about their ventures that are unknown to potential resource providers (receivers). Signals, particularly those of low cost, are used by entrepreneurial ventures to reduce information asymmetries and avoid market failure (Courtney, Dutta, & Li, 2017). Indeed, research shows that entrepreneurial ventures - which lack a track record of financial performance - utilize low cost signals (e.g., narratives) to obtain external resources because they are effective at reducing information asymmetries and easier to produce than high cost signals (e.g., human capital) (Anglin et al., 2018; Mahmood, Luffarelli, & Mukesh, 2019).² Research supports the idea that signals effective at reducing information asymmetries are important for accessing resources in entrepreneurial contexts, including angel investing (Cardon, Mitteness, & Sudek, 2017), venture capital (Howell, 2020), initial coin offerings (Fisch, 2019), and crowdfunding (Anglin et al., 2018), to name a few.

² Research on signaling theory discusses the importance of signal cost with respect to signal quality and effectiveness. In the entrepreneurial venture context, potential resource providers prefer high-cost signals over low-cost signals, but ventures often rely on low-cost signals out of necessity. Connelly et al. (2024) and Bafera & Kleinert (2023) provide a thorough review of signal cost, quality, and effectiveness.

Second, the integration of signaling theory with decision-making heuristics provides unique insights into how signals can influence the speed of decision-making and ultimately the final judgment on a contract research proposal. Heuristics help explain how individuals and firms use simplified processes to improve decision-making efficiencies in uncertain environments (Artinger et al., 2015). In the context of our study, resource providers have limited objective information about an entrepreneurial venture, and we argue that the language embedded in EOL and COL serves as implicit cues that influence and simplify the decisions of resource providers. The converging logic of signaling theory and decision-making heuristics is that when information asymmetries are prevalent and decision-making is subjective, the signaling provided by insiders simplifies the decision-making of outsiders (Petty, Gruber, & Harhoff, 2023; Spence, 1973). Research on crowdfunding supports our thesis that narratives influence outsiders. Indeed, studies show how storytelling (Geiger & Moore, 2022), positive narratives (Anglin et al., 2018), and language suggesting quality and competence (Moradi, Dass, Arnett, & Badrinarayanan, 2024) are associated with crowdfunding outcomes and ultimately access to external financial resources.

We apply a similar logic in our study based on signaling theory and decision-making heuristics, albeit with an emphasis on non-financial capital resources and how signaling can influence the duration or speed of the decision-making process (Bakker & Shepherd, 2017). Based on the logic of existing theoretical frameworks, we posit that narratives will play a significant role when accessing non-financial capital resources. Using the context of contract research proposals, we theorize that EOL and COL will influence the decision speed of resource providers.

Entrepreneurial-oriented language (EOL) and speed to decision. Entrepreneurial ventures that show high levels of entrepreneurial orientation (EO) can influence the decision-making processes of resource providers (Calic & Schevchenko, 2020). Ventures that signal high

EO provide cues to resource providers that highlight the ventures' ambitions, motives, and abilities regarding the mobilization of resources, exploitation of opportunities, and likely performance as an entrepreneurial venture (Clausen & Korneliussen, 2012; Moreno-moya & Munuera-aleman, 2016; Shan, Song, & Ju, 2016). Since entrepreneurial ventures possess more information than resource providers, EOL embedded in contract research proposals is a central mechanism to convey this information to reduce information asymmetries (Martens et al., 2007; Moss et al., 2015; Sahaym et al., 2021; Wang, Malik, & Wales, 2021). Communicating effectively is important not only for the resource seekers to gain access to resources, but also for the resource providers who want to make rational decisions but are constrained by a lack of comprehensive and objective information about the venture. Based on the logic of decision-making heuristics (Artinger et al., 2015), we argue that proposals higher in EOL will influence the perceptions of resource providers in a way that prompts faster decision-making regarding the ventures EO. Cues regarding EO will influence perceptions of an innovative opportunity with high potential for rewards in which resource providers can choose to accept (reject) a proposal to act on (avoid) a potential opportunity. EO cues such as proactivity and risk-taking signal to resource providers the ambitions of the resource seekers, which could attract them to (or deter them from) contracting with the venture. In general, theory regarding decision-making heuristics and signaling supports the idea that higher levels of EO cues in proposal narratives are likely to reduce information asymmetries in entrepreneurship contexts. As such, contract research proposals higher in EOL are likely to support the decision-making efficiencies of resource providers in a manner that supports faster decisionmaking. Conversely, proposals lower in EOL provide fewer EO cues and are likely to be less effective at mitigating noisy information, which can impede the decision-making process (Kruse, Bendig, & Brettel, 2023). Based on the above theorizing, we offer the following hypothesis:

Hypothesis 1. There is a positive association between entrepreneurial-oriented language (EOL) in contract research proposals and speed to decision.

Cognitive-oriented language (COL) and speed to decision. COL represents the degree to which a narrative includes words that are rational and intellectual (Moradi et al., 2024). COL can be used to signal the value of an opportunity (Xiang, Zhang, Tao, Wang, & Ma, 2019) and can be influential on individuals' decision-making in contexts replete with information asymmetries. For instance, COL is argued to influence the perceptions of resource providers by instilling confidence and reducing uncertainties about the information portrayed in a narrative (Moradi et al., 2021). COL can provide resource providers with a more vivid understanding of an opportunity and can increase cognitive engagement with and knowledge about information in a proposal (Cho, Im, Fjermestad, & Roxanne Hiltz, 2003). Moreover, COL is suggested to improve the quality of information being offered to the resource providers, which can influence their trust in the narrative of a proposal (Moradi et al., 2024). In general, proposals higher in COL will convey information in a way that is clearer and more trustworthy to resources providers, thus supporting their decisionmaking efficiencies. Conversely, proposals lower in COL are less clear, and it may require extra effort by resource providers to understand or trust in the information provided in the proposals. Based on this theorizing, we offer the following hypothesis:

Hypothesis 2. There is a positive association between cognitive-oriented language (COL) in contract research proposals and speed to decision.

Decision speed and proposal outcome. Above we hypothesized that EOL and COL provide cues to resource providers that support the efficiencies of their decision-making processes regardless of the ultimate decision to accept or reject a proposal. There are reasons, however, why we should expect speed to decision to show a positive association with acceptance rather than rejection of a contract research proposal. Inherent in our theorizing, decision-making efficiencies are improved through mechanisms related to EO cues (e.g., being entrepreneurial) and CO cues (e.g., high quality information) as they improve the clarity of the opportunity being presented. Proposals lacking these cues increase the amount of noisy information (Kruse et al., 2023). The lack of cues creates more cognitive load and cognitive strain on academic scientists, who are already constrained by their formal responsibilities (e.g., research and teaching), which can impede their ability to form a final judgment about the opportunity (Zacharakis & Meyer, 1998). Proposals that are less clear about an opportunity will sit longer as resource providers are not confident about what they will be accepting or rejecting. Consequently, the longer a proposal goes without a decision, the attention of resource providers directed at the proposal is likely to dissipate. A key tenet of the Attention Based View (ABV) of decision-making (Ocasio, 1998; see Brielmaier & Friesl, 2023, for a review) states that the behavior of decision-makers "depends on what issues and answers they focus their attention on" (Ocasio, 1998: 188). Consistent with the ABV, we argue that as indecision is prolonged, competing interests and new opportunities will arise, thus drawing attention and motivation away from the focal opportunity. Indeed, entrepreneurship and entrepreneurial venture contexts are replete with fleeting and emerging opportunities. As attention moves away from a proposed opportunity, the more likely it will be rejected as competing interests and new opportunities gain the attention of decision-makers. Consistent with a key tenet of ABV, we argue that faster decision-making is more likely – on average – to result in acceptance rather than rejection in the context of contract research proposals. Based on this logic, and theory rooted in decision-making, we provide the following hypothesis:

Hypothesis 3. There is a positive association between speed to decision and contract research proposal acceptance (vs. rejection).

METHODS AND DATA

Sample and Procedures

To examine our hypotheses, we analyzed a unique dataset of 3,422 industry-initiated contract

research proposals submitted to Interface – a Scottish government-funded 'broker'/ 'intermediary' organization (Clayton et al., 2018). Interface works closely with entrepreneurial ventures to prepare a contract research proposal within specific scientific fields. Once a venture indicates that they require contract research support to access non-financial capital resources (i.e., academic knowledge/expertise and/or access to university laboratories/facilities) and develop their opportunity, Interface provides the venture with a contract research proposal template for completion. Within the contract research proposal, the venture is required to develop a narrative centered on a full description of their specific opportunity (including the associated innovation and impact arising from the opportunity), their venture background and wider market background, and the academic resource expertise sought to progress the specific opportunity.

Upon completion of the contract research proposal narrative, Interface distributes the contract research proposal to Scotland's twenty-three higher education and research institutes. Proposals are then forwarded directly to the relevant academic scientist, who decides whether to accept or reject the contract research proposal. If an academic scientist expresses interest in a proposal, Interface coordinates contract negotiations, usually via the relevant university technology transfer office (TTO). There are no deadlines imposed on the relevant university academic to provide a decision (acceptance or rejection). Contract research proposals, including the language employed within them, serve as the primary conduit between the venture and the academic scientist. Therefore, they are an appropriate setting to investigate how the language utilized within contract research proposals affects the speed to decision and proposal outcome.

Using Linguistic Inquiry and Word Count (LIWC) software (Pennebaker et al., 2001), we conducted textual analysis of 3,422 industry-initiated contract research proposals to explore the speed to decision (i.e., the time taken for an academic to accept or reject the industry-initiated

contract research proposal). Studies show LIWC to be useful in investigating the emotional, cognitive, and entrepreneurial-oriented discourse of narratives (Johnson, Bock, & George, 2019; Titus et al., 2020; Wolfe & Shepherd, 2015). Specifically, studies utilize LIWC to explore how emotional, cognitive, and entrepreneurial oriented discourse influences access to financial capital resources (Kim et al., 2016; Moradi & Badrinarayanan, 2021; Moss et al., 2015; Parhankangas & Renko, 2017; Wales & Mousa, 2016).

Variables

Independent variables. In alignment to previous studies (e.g., Johnson et al., 2019; Titus et al., 2020; Wales & Mousa, 2016; Wolfe & Shepherd, 2015) we focus on EOL and COL as our independent variables (Calic & Schevchenko, 2020; Kim et al., 2016; McKenny et al., 2018; Moradi & Badrinarayanan, 2021; Moss et al., 2015; Parhankangas & Renko, 2017). Within LIWC, the dictionary for COL contains 730 unique individual words, such as think, consider, perhaps, could, and always. The COL consists of several sub-dimensions, including *insight, causation, discrepancy, tentative, certainty*, and *differentiation* (Pennebaker et al., 2001; Tausczik & Pennebaker, 2010), which we used for the current study. For EOL, we utilized the entrepreneurial-oriented dictionary within LIWC developed by Bliemel, D'Alessandro, de Klerk, Flores, Harrison, & Miles (2021). The EOL consists of several sub-dimensions, including *risk, creative, optimistic, reward, innovative, and proactive*. COL and EOL are quantified using the LIWC output, which consists of standardized word counts (Moss et al., 2018).

Dependent/mediator variables. Speed to decision was assessed as the time taken between the date a contract research proposal was submitted to the date a contract research proposal was either accepted or rejected. Time between dates was measured in days and reverse coded to represent *speed to decision*. Proposal accepted was coded with respect to whether a contract research proposal was accepted (proposal accepted = 1) or rejected (proposal rejected = 0).

Control variables. We considered several control variables that research identifies as having an influence on decision-making in resource seeking and venture contexts. We controlled for *number of words* in a contract research proposal, as longer descriptions allow entrepreneurs to provide more information in their proposals (Moss et al., 2018). We also controlled for the affective and gendered tone of proposal narratives, as both affect and gender can influence resource acquisition in entrepreneurship contexts (Anglin et al., 2018; Geiger & Oranburg, 2018). Affective tone was assessed by examining proposals for keywords reflecting positive tone (e.g., happy, inspired, hope) and negative tone (e.g., sad, fear, pressured). Gendered tone was assessed by examining proposals for female (e.g., her, she, woman) and male (e.g., he, him, men) references. Lastly, we controlled for the size and location of the venture (local SME [small and medium sized *enterprise*]; 1 = yes, 0 = no) since this may influence the decision-making processes of contract reviewers. For example, prior research shows firm size to influence university-industry engagement (Fontana, Geuna, & Matt, 2006; Goel, Göktepe-Huttén, & Grimpe, 2017) and emphasizes the importance of geographical proximity on university-industry engagement (D'Este, Guy, & Iammarino, 2013; Laursen, Reichstein, & Salter, 2011) and contract research (Spithoven et al., 2020). We also controlled for the time of year that a proposal was opened based on common academic calendars (e.g., Fall, Spring, Summer dummy variables) as this could influence the decision-making of the academic scientists.

Industry sector. 34 industry sectors were considered as control variables since industry sector is important in determining university-industry engagement activities (Bekkers & Bodas-Freitas, 2008; Spithoven et al., 2020). Including each of these industry sectors as a control variable would result in the addition of 34 variables (i.e., 1/0 coding for each industry). Given the quantity of industry sectors, we treated observations as nested within industry sectors as opposed to treating

each industry as an individual control variable. Clustering approaches are recommended when there are many industry segments to reduce degrees of freedom and improve statistical power (Hough, 2006). Examining the dataset in this way is consistent with literature that recommends clustering methods to examine nested datasets (McNeish, Stapleton, & Silverman, 2017). As such, we account for industry effects by examining the proposed model in *Mplus* 8.7 using the *Type* = *Complex* function and setting *Cluster* = *Industry* to account for the nonindependence of observations (Muthén & Muthén, 1998-2021). See Appendix A for additional information about the industries.

ANALYSES AND RESULTS

Validating the Independent Variables (EOL and COL)

We assessed the psychometric properties of COL and EOL variables by examining their factor structure, validity, and reliability as a reflective construct. Following best practice recommendations (Hinkin, 1998), we used the split-sample method of factor analysis by randomly splitting the full sample into two subsamples. First, we conducted an exploratory factor analysis (EFA) with Subsample 1 to examine the factor structure of the COL and EOL indicators. Next, an identified factor structure was further examined using confirmatory factors analysis (CFA) with Subsample 2. Hinkin (1998) recommends a structural equation modeling approach to CFA, which allows for a stricter interpretation of unidimensionality than does EFA. As such, we employed CFA using structural equation modeling methodology in *Mplus* 8.7 (Muthén & Muthén, 1998-2021). Lastly, the internal consistency of the cognitive- and entrepreneurial-oriented variables were examined with respect to the recommended cutoff of .70 (Hinkin, 1998). The results of all validity analyses are reported in Appendix B.

EFA were performed using a principal axis with promax rotation (Hinkin, 1998) in SPSS. Results for COL showed three factors with eigenvalues greater than one that explained a cumulative variance of 69.2% in the COL construct. Three of the COL indicators loaded on Factor 1, three indicators on Factor 2, and a single indicator on Factor 3. The results also reveal a cross-loading of one item between Factor 1 and Factor 2, and loadings with opposite signs (positive, negative) in Factor 2. Taken together, the EFA results suggest that it would be inappropriate to treat the COL indicators as reflecting a higher order construct. This interpretation was further supported by a CFA analysis on Subsample 2, which showed a mix of large, small, positive, and negative λ values ($\chi^2_{(df)} = 482.33_{(9)}$, RMSEA = 0.18, CFI = 0.41, SRMR = 0.09). Moreover, a reliability analysis of the full sample showed poor internal consistency (Cronbach's $\alpha = .23$).

EFA results for EOL showed two factors with eigen values greater than one that explained a cumulative variance of 77.2% in the EOL construct. Six of the EOL indicators loaded on Factor 1 and one EOL indicator loaded on Factor 2. All loadings were positive and exceeded the recommended cut-off of .40 (Hinkin, 1998). Moreover, there were no cross-loadings across factors. However, Factor 2 consisted of only a single loading (i.e., uncertainty). As a result, the single loading on Factor 2 was dropped and a second EFA was examined for the EOL construct. The results indicated a single factor with an eigenvalue greater than one that explained a variance of 71.8% in the EOL construct. All loadings were positive and exceeded .40. The EFA results supported the validity of EOL as a reflective construct using six out of the original seven EOL indicators. Additional support was found by a CFA analysis on Subsample 2, which showed that the λ values for all items were both large (\geq .30) and significant (p < .05; Djurdjevic et al., 2017; $\chi^2_{(df)} = 964.018_{(9)}$, RMSEA = 0.25, CFI = 0.96, SRMR = 0.07).³ Moreover, a reliability analysis of the full sample showed good internal consistency (Cronbach's $\alpha = .92$).

³ Our RMSEA value is higher than what is typically considered a good RMSEA value. Research suggests that a model should not be ruled insufficient based on a single index (e.g., Wang & Ford, 2020). Moreover, research has recommended not reporting RMSEA under some circumstances (i.e., Kenny, Kaniskan, & McCoach, 2015). All considered, EOL passed the validity tests for our study.

Based on the above results, support was not found for the COL variable as a reflective construct. As such, COL indicators were examined individually in the main analyses. Support was found for EOL as a reflective construct. Following best practice recommendations, we took an additional step to examine EOL's predictive validity as a reflective construct (Short et al., 2017). Using the split sample methodology described above, we examined the set of EOL dimensions and their associations with speed to decision while controlling for whether a firm was a local SME (1 = yes; 0 = no). The results of structural equation modeling showed that the set of EOL dimensions significantly explained variance in speed to decision for both Subsample 1 and Subsample 2 with R^2 s of .08 (p < .01; $\chi^2_{(df)} = 0.00_{(0)}$, RMSEA = 0.00, CFI = 1.00, SRMR = 0.00) and .05 (p < .01; $\chi^2_{(df)} = 0.00_{(0)}$, RMSEA = 0.00, SRMR = 0.00), respectively. The pattern of associations was consistent for both subsamples.

Examining Hypotheses

Table 1 displays the means, standard deviations, and correlations among all variables. With respect to hypotheses, there was a positive association between EOL and *speed to decision* (r = .20), and positive associations for the COL components *causation* (r = .17), *certainty* (r = .15), and *differentiation* (r = .11) with *speed to decision*. Negative associations were found for the COL components *insight* (r = .20), *discrepancy* (r = .10), and *tentative* (r = .12) with *speed to decision*. A positive association was found between *speed to decision* and *proposal accepted* (r = .45).

Insert Table 1 about here

Regarding control variables and *speed to decision*, positive associations were found for *number of words* (r = .35), *positive affective tone* (r = .24), *negative affective tone* (r = .02), *female gendered tone* (r = .07), *male gendered tone* (r = .05), and *local SME* (r = .16). For proposal

accepted, positive associations were found for number of words (r = .08), positive affective tone (r = .02), male gendered tone (r = .01), local SME (r = .10), and proposal opened in the Fall (r = .03). Negative associations were found for negative affective tone (r = .02), female gendered tone (r = .01), and proposals opened in the Spring (r = .03).

Variables were examined for skewed distributions prior to the main analyses used to examine the hypotheses. Transformations were used to normalize variables that showed a skewness statistic greater than one. This resulted in a natural log transformation of *speed to decision*. We used the inverse hyperbolic sine transformation for *negative affective tone, female gendered tone*, and *male gendered tone* which is recommended for variables that include zero values (Anglin, Short, Ketchen Jr, Allison, & McKenny, 2020).

Table 2 depicts the structural equation modeling results of *Mplus* 8.7 (Muthén & Muthén, 1998-2021). Model 1 includes controls only in predicting *speed to decision* and *proposal accepted* $(\chi^2_{(df)} = 0.00_{(0)}, RMSEA = 0.00, CFI = 1.00, SRMR = 0.00)$. Model 2 shows the results examining Hypotheses 1 through 3 $(\chi^2_{(df)} = 39.50_{(7)}, RMSEA = 0.04, CFI = 0.98, SRMR = 0.02)$. Results showed a positive association between EOL and *speed to decision* ($\beta = .07, p < .01$), supporting Hypothesis 1. With respect to Hypothesis 2, individual components of COL were not valid indicators of a parent construct and therefore were examined individually. Results showed a positive association between *causation* and *speed to decision* ($\beta = .07, p < .01$), which was consistent with Hypothesis 2, whereas *insight* showed a negative association with *speed to decision* ($\beta = .08, p < .01$), which was contradictory to Hypothesis 2. Other COL components (*discrepancy*, *tentative*, *certainty*, and *differentiation*) were not significant. The results showed a positive

association between *speed to decision* and *proposal accepted* ($\beta = .50$, p < .01), supporting Hypothesis 3.^{4, 5}

Insert Table 2 about here

Brief Overview of the Results

The results of this study suggest that EOL has a robust positive association with *speed to decision* in the context of contract research proposals. Moreover, EOL was found to be a validated reflective construct for research on narratives. With respect to COL facets, there was a positive association between *causation* and *speed to decision* and a negative association between *insight* and *speed to decision*. COL was not validated as a reflective construct, however, as it failed the validity tests in this study. As such, we examined COL components within the scope of Hypothesis 2 but could not provide a direct test of the hypothesis. The results ultimately suggest that *speed to decision* has a strong and robust association with *proposal accepted*, suggesting that *speed to decision* plays a key theoretical role in explaining the connection between the language of a proposal (e.g., EOL) and proposal success.

Lastly, some of the significant control variables should not be ignored as they inform similar phenomena of other entrepreneurship contexts. For instance, a proposal's *positive affective tone* and *number of words* had a positive association with *speed to decision*, which informs

⁴ We performed a bootstrap analysis of the hypothesized associations (500 random resampling with replacement) to provide a more rigorous test of the findings (Williams & Shepherd, 2016). We also performed a series of tests to assess the robustness of the results. Both the bootstrapping results and robustness tests provide additional support of the findings. Results are provided in Appendix C.

⁵ In our research, we propose and examine a model based on indirect effects hypotheses (Mathieu & Taylor, 2006). The term indirect effects and mediation are often used interchangeably but are examined in different ways. Indirect effects, as opposed to partial mediation effects, do not assume a direct effect between the X and Y variables in an $X \rightarrow M \rightarrow Y$ path model. To provide insights into this issue as it relates to our study, we performed a 'post hoc' analysis and we explain why direct effects between the X and Y variables are not included in our model. Analyses and explanations are provided in Appendix D.

research in the venture funding context (Anglin et al., 2018; Patel, Wolfe, & Manikas, 2021). The *local SME* variable also showed a positive association with *speed to decision*, thus informing literature on the proximity or size of a business and venture outcomes (Broström, 2010; D'Este et al. 2013; Fontana et al., 2006; Goel et al., 2017; Laursen et al., 2011).

DISCUSSION

We set out to understand how language utilized within university-industry contract research proposals influences academic scientists (i.e., resource providers) to accelerate their speed to decision and ventures (i.e., resource seekers) to enhance their non-financial capital resource mobilization (i.e., proposal acceptance). Our findings have important implications for entrepreneurship theory, practice, and policy. Specifically, we contribute to theory rooted in narratives' influence on decision-making (Anglin et al., 2018; Artinger et al., 2015; Moradi et al., 2024), cultural entrepreneurship scholarship (Jancenelle et al., 2019; Lounsbury & Glynn, 2001; Martens et al., 2007) and university-industry engagement (Perkmann et al., 2013; 2021), which we elaborate on below.

Implications for Theory and Practice

Non-financial capital resource mobilization: Language and speed. Our study builds upon research on entrepreneurial venturing and resource mobilization (Clough et al., 2019; Lounsbury & Glynn, 2001) by providing evidence on the relationship between language and speed to access non-financial capital resources. By specifying this link, we respond to recent calls to further consider the role of time (i.e., speed to decision) in the mobilization of resources (Thornton et al., 2019; Zahra, 2021). At the same time, we build upon prior research (Short et al., 2017; Wales & Mousa, 2016) to show that the relationship between EOL and COL holds beyond financial capital resource acquisition. Our findings support theorizing rooted in the influence of language-based cues on decision-making heuristics (Kruse et al., 2023) and support the findings of recent studies showing that narratives play an important role in the decision-making of resource providers (Geiger & Moore, 2022; Moradi et al., 2024).

Our study reveals how language can influence the speed to decision by resource providers, and the subsequent resource access by requesting ventures. Specifically, we show that contract research narratives containing EOL and certain COL components provide cues to resource providers. Specifically, the results support the idea that EOL is an effective tool for improving access to resources. Our results also suggest that certain forms of COL influence access to resources, albeit in different ways. Notably COL reflecting 'causation' is more likely to speed up access to resources, which is consistent with what our theorizing suggests. Indeed, causation language affords resource providers with project-specific information, addressing the 'how' and 'why' questions, and reduces uncertainties and information asymmetries. In doing so, it provides important cues that improves resource providers' information processing and interpretation efficiencies that supports speed to a final judgment (Zacharakis & Meyer, 1998; Zhang, Aerts, & Pan, 2019). In contrast, language reflecting 'insight' shows a negative association with decisionmaking speed, which is opposite to what our theorizing suggests. One explanation for this finding is that insight language imbues contract research proposals with a subjective assessment of the underlying opportunity, rather than providing an objective factual assessment. Whilst to some extent this subjectivity can help emphasize the merits of the opportunity, it may also result in an increase in noisy information (Kruse et al., 2023) and reduce the clarity of the opportunity. Accordingly, resource providers require more time to decipher the subjective from the objective and spend more time questioning the viability of an opportunity (Kim et al., 2016), resulting in slower decision-making speed. Based on the above and consistent with the ABV (Brielmaier &

Friesl, 2023; Ocasio, 1998), we reveal a positive association between speed to decision and contract research proposal acceptance.

Resource orchestration and mobilization for entrepreneurial ventures incorporates a range of resources. Theory addresses how narratives help ventures leverage resources from investors (Blevins et al., 2019; Martens et al., 2007; Van Werven, Bouvmeester, & Cornelissen, 2019) and 'the crowd' (Geiger & Moore, 2022; Manning & Bajarano, 2017; Moradi et al., 2024; Short et al., 2017). This literature highlights the importance of mobilizing financial capital rather than mobilizing non-financial capital resources. At the same time, the use of narratives to leverage resources almost predominantly focuses on online crowdfunding pitches. Our study addresses these two gaps in the research on ventures' resource orchestration and mobilization; it reveals how EOL and COL components, within less traditional narrative mechanisms (i.e., contract research proposals), influence the speed at which non-financial capital resources (i.e., academic knowledge/expertise and/or access to university laboratories/facilities) are mobilized. In doing so, we build upon research exploring the use of language within pitches to mobilize resources (Anglin et al., 2018; Moss et al., 2018; Parhankangas & Renko, 2017; Short et al., 2017), as well as IPO prospectuses (Blevins et al., 2019; Wales & Mousa, 2016). We also enrich recent research that emphasizes the need to look beyond how narratives persuade early-stage investors by considering how narratives influence later-stage resource providers (Chapple, Pollock, & D'Adderio, 2021).

Our findings reveal practical implications for entrepreneurial ventures. Specifically, since we show that contract research proposals displaying EOL and certain COL components determine decision-making speed and proposal acceptance, ventures may want to think of communication skills as a desirable capability that should be developed and/or acquired to support venture efforts. Additionally, ventures should consider how they communicate to salient stakeholders, as underestimating the importance of communication-related capabilities will likely delay access to critical resources, which can have detrimental effects on the venture's activities and performance. Accordingly, investing time and resources into crafting narratives could lead to an important dynamic capability for ventures (Helfat & Peteraf, 2015; Teece, Peteraf, & Leih, 2016).

The language of contract research. Our focus on the relationship between contract research language, decision-making speed, and successful contract research outcomes, advances our understanding of university-industry engagement scholarship (Perkmann et al., 2013; 2021; Spithoven et al., 2020). As suggested by the findings of this study, contract research proposal language that supports the decision-making heuristics of academic scientists can improve the likelihood of proposal acceptance. Prior research has not explicitly tested this relation. This is problematic; not exploring this relationship can impede theoretical progress in explaining university-industry engagement and prevents us from realizing the full benefits of universityindustry engagement activities. In particular, for resource-constrained ventures, contract research is critical to secure slack resources and drive innovative activities (Anckaert & Peeters, 2023; Goel et al., 2017; Stevenson, Kier, & Taylor, 2021). Since contract research proposals, including the language employed within them, serve as the primary conduit between the industry partner and the academic scientist, understanding how entrepreneurial ventures can utilize language to persuade academics to engage is imperative. Our findings reveal that ventures can speed up access to non-financial capital resources when adopting EOL and specific COL within contract research proposals.

Implications for Policy

Our study reveals several important policy implications for the support of entrepreneurial ventures, and their academic partners. First, our research reveals how ventures can craft and employ language such as EOL and COL components to expedite decision-making. Responding to calls for proposals is a core activity for most, if not all, R&D-intensive ventures. The prevailing wisdom is that speed matters for entrepreneurial ventures (Bakker & Shepherd, 2017; Dykes, Huges-Morgan, Kolev, & Ferrier, 2019; Zahra, 2021). Therefore, a possible differentiator for ventures is developing capabilities related to language protocols that persuade resource providers to make faster decisions and thus release resources quicker.

Accordingly, it is important that governments and NGOs incorporate language capabilities into programs that support entrepreneurial activities. Specifically, in the case of contract research language-related capabilities, we reveal that EOL that showcases the opportunity to be *creative*, *innovative*, *rewarding*, *proactive*, and *low risk* is more likely to result in positive outcomes. At the same time, *causation* language that provides knowledge relating to the opportunity's possible/predictable futures (Sarasvathy, 2001) and pathways to impact (Chen, Sharma, & Munoz, 2023), is again more likely to result in positive university-industry engagement outcomes. In contrast, too much excessively detailed, in-depth *insight* relating to the opportunity should be avoided since we show this to be related to unsuccessful university-industry engagement outcomes. The interplay between language-related capabilities, opportunities, and speed has important implications for leveraging entrepreneurial ecosystems (Dimov, 2020).

Second, brokerage organizations such as Interface, who are charged with facilitating contract research proposals, will need to develop their own language-related capabilities. Academics and commercial partners speak a different 'language,' partly due to differing institutional logics (Perkmann et al., 2019). Therefore, in working with both commercial and academic stakeholders, brokerage organizations should strive towards establishing common ground – a shared language between both stakeholders – which has been shown to support resource orchestration and mobilization (Alvarez & Sachs, 2023). Specifically, helping commercial clients

to craft contract research proposals that establish common ground, such as proposals consisting of EOL and certain COL components, will increase decision-making speed and the likelihood of proposal acceptance. This will allow brokerage organizations to increase their bandwidth, improve internal efficiencies, and the quantity and quality of their opportunities-client matching.

To date, our understanding of brokerage organizations and their impact on science commercialization activities is rather limited (Clayton et al., 2018); however, our findings can support brokerage organizations in influencing policy through agenda setting. Specifically, brokerage organizations can drive successful university-industry engagement activities, which play a critical role in supporting the mission of entrepreneurial universities (Meek & Gianiodis, 2023), the emergence and development of university-centered entrepreneurial ecosystems – UCEEs (Johnson et al., 2019; 2023), and wider societal impacts (Fini et al., 2018). Given austerity measures implemented by governments, brokerage organizations that utilize the findings from our research to improve academic-industry engagement activities are well-positioned to lobby governments into continuing to fund their organizations and associated program of activities. Specifically, in establishing common ground between stakeholders, brokerage organizations can enhance their support of entrepreneurial ventures to develop their products and services through access to critical resources (Alvarez & Sachs, 2023).

Third, our study has implications for entrepreneurial universities and their associated TTOs. Given entrepreneurial universities' commitment to driving forward commercial activities at the university-industry boundary (Meek & Gianiodis, 2023), our findings shed light on the importance of carefully crafting language to successfully engage academics in university-industry activities. Incentives alone for engaging in commercial activities are simply not sufficient (Markman, Gianiodis, Phan, & Balkin, 2004). In fact, our research shows that language – namely

EOL and COL – also plays a critical role in facilitating academic-industry activities. Therefore, entrepreneurial universities and TTOs should offer formal training and support programs to academic scientists and student entrepreneurs to prepare them for commercial engagement with partners (Harima & Harima, 2024; Johnson & Bock, 2017; Johnson et al., 2019).

Ultimately, the public policy considerations are clear; language-based capabilities can lead to important translational activities and regional economic and social impacts (Fini et al., 2018). Whilst prior research focuses on the microfoundations of university commercialization activities and associated policy implications (Balven et al., 2018; Hmieleski & Powell, 2018), our study builds upon this research by introducing language and proposals into this body of research. Whilst some universities and TTOs implement policies centered on incentivizing academics to engage with industry partners (Abramo & D'Angelo, 2022), our findings can support policies centered on university-industry communication processes and the most effective language to use to persuade academics to engage with industry.

Limitations and Future Directions

We are cognizant of the limitations of our research, which future research can address. First, whilst our study reveals how the narrative discourse of contract research proposals determines the speed to proposal acceptance or rejection, we do not have further data on whether the specific proposal led to a successful innovation. Future research may conduct longitudinal methodologies that tracks the pathway of the innovation from contract research proposal acceptance/rejection to new product/service development.

Second, our study does not have performance data on the venture; we do not know what implications speed to decision has on the performance of the venture. Knowing this outcome would be useful given that the goal of resource mobilization is to execute an opportunity that will drive value creation and venture performance. Future studies are encouraged to consider the relationship between decision speed, non-financial capital resource mobilization, and performance in entrepreneurial ventures. Whilst there is a rich body of research exploring human capital and entrepreneurial success (Crook, Todd, Combs, Woehr, & Ketchen Jr., 2011; Marvel, Davis, & Sproul, 2016; Unger, Rauch, Frese, & Rosenbusch, 2011), future research could explore how speeding up access to non-financial capital resources, notably human capital, can influence entrepreneurial opportunity development and venture performance.

Third, whilst our study offers a novel quantitative computational linguistic analysis, augmenting this with qualitative data would provide additional richness to the decision speed-resource mobilization relationship examined in this study. Interview data that teases out academic motivations and decision-making processes for engaging in contract research would be a fruitful avenue for further research. At the same time, further information relating to the individual characteristics of academic scientists and the specific university would be beneficial. For example, since academics' entrepreneurial experience and seniority (Perkmann et al., 2021), and university culture (Johnson & Bock, 2017; Johnson & Mackenzie, 2021) influence commercial activities, future research could glean information relating to the academic scientists/university to understand if/how these academic/university characteristics interact with decision-making speed and resource mobilization.

Fourth, consistent with research in organizational sciences, we caution interpretation of causality (Alterman, Bamberger, Wang, Koopmann, Belogolovsky, & Shi, 2021; Teodorovicz, Lazzarini, Cabral, & Nardi, 2023; Witt, Fainshmidt, & Aguilera, 2022). While the structure of our data inherently provides a temporal sequence (e.g., proposal submission precedes decision-making), future research may want to further address causal mechanisms of EOL signals and decision-making speed as well as decision speed's association with decision outcomes using lab

experiments or experience sampling methods. In a similar vein, our methods do not allow for an examination of the micro-mechanisms of decision-making. We acknowledge the complexity of decision-making processes across individuals, which include cognition, emotion, motivation, personality, among other individual differences. These within individual processes also interact with external factors such as time pressure, work-life balance, conflicting responsibilities etc. Future studies can investigate the EOL-decision speed mechanism by examining decision makers cognition, emotion, and motivation as well as other individual (e.g., personality, demographics) and external factors (e.g., work-life balance, work environment). Furthermore, our study relies on a social science-wide limitation of imperfect proxies (Soublière, Lo, & Rhee, 2024). For instance, in the context of our study, we use time between 'proposal submission' to 'acceptance or rejection of a proposal' as a proxy of the time it takes for a judgement to be made on a proposal. While imperfect, however, this proxy is consistent with other measures across the management and organizational sciences when examining decision speed (e.g., Bakker & Shepherd, 2017; Petty et al, 2023).

In summary, we found a positive association of EOL and specific elements of COL with decision-making speed, which in turn shows a positive association with proposal acceptance. Importantly, these language elements seem independent of other explanations for decision speed, which suggests that narratives are a critical dynamic capability for acquiring and mobilizing non-financial resources. While this study surfaces important insights, it is only the start. We hope it is a catalyst for future research.

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TABLES AND FIGURES

	М	SD	1	2	3	4	5	6	7	8	9	10
Dependent variable												
Proposal accepted	0.37	0.48										
Mediator variable												
Speed to decision ^a	-829.34	1059.29	.45									
•												
Independent variable												
EOL (reflective) ^b	0.75	0.40	.02	.20								
COL (LIWC												
components) °												
Insight	2.58	0.78	04	20	17							
Causation	2.22	0.94	.05	.17	.11	22						
Discrepancy	1.59	0.52	04	10	14	.17	10					
Tentative	2.25	0.59	- 03	- 12	- 10	.18	- 07	.39				
Certainty	0.86	0.34	.00	.15	.10	.03	.00	.03	- 12			
Differentiation	1 78	0.56	- 02	11	07	- 13	22	23	44	08		
Differentiation	1.70	0.50	.02		.07	.15	.22	.20		.00		
Contract controls												
Number of words	945.04	370.04	.08	.35	29	- 42	39	- 22	- 26	.11	20	
Affective tone	, 10101	270101	.00				,		.20		.20	
Positive	2.98	0.83	02	24	36	- 11	14	- 07	- 08	11	07	31
Negative	0.33	0.35	- 02	02	- 10	01	08	- 05	- 04	07	.07	15
Gendered tone	0.55	0.55	.02	.02	.10	.01	.00	.05	.04	.07	.07	.15
Female	0.05	0.21	- 01	07	04	- 05	09	- 01	- 04	03	02	14
Male	0.05	0.17	.01	.07	03	- 07	.02	- 03	- 05	.03	.02	07
Wale	0.00	0.17	.01	.05	.05	07	.02	05	05	.05	.01	.07
Season controls												
Fall	33	47	03	03	06	- 06	02	- 02	05	00	05	05
Spring	.33	.17	- 05	- 03	- 03	.00	- 01	.02	- 01	- 03	- 05	- 03
Summer	.54	.47	05	05	03	.00	01	.05	- 05	03	05	03
Summer	.54	.47	.02	.00	05	.00	01	.00	05	.02	.01	01
Firm controls												
Local SMF ^d	0.81	0.30	10	16	10	- 11	13	00	- 04	13	03	10
Industry ^e	-	-	.10	.10	.10		.15	.00	-0.	.15	.05	.10
Industry ^e	-	-	-	-		11	-	-	0+		-	

TABLE 1 Means, Standard Deviations, and Correlations

N = 3415-3422. Pairwise deletion. ^a Speed to decision = number of days; reverse scored so that a positive correlation indicates a faster speed to decision. ^b Past the validity tests as a reflective construct; reflects an overall construct that is comprised of the following EOL components: risk, creative, optimistic, reward, innovative, and proactive. ^c Failed the validity tests as a reflective construct; analysis is performed on each individual COL component. ^d Local SME is operationalized as Scottish venture with up to 250 employees. ^e Ventures represented a total of 34 industry sectors; industry descriptive statistics are provided in Appendix A. EOL = Entrepreneurial-oriented language. COL = Cognitive-oriented language. LIWC = Linguistic Inquiry and Word Count. SME = Small and medium sized enterprise. Proposal accepted (1 = yes; 0 = no). Local SME (1 = yes; 0 = no).

p < .01; correlations of $r \ge |.045|$.

p < .05; correlations greater than $r \ge |.034|$.

TABLE 1 (continued).

	11	12	13	14	15	16	17
Negative	07						
Gendered tone							
Female	.13	.03					
Male	.04	.01	.06				
Season controls							
Fall	.03	.02	.00	01			
Spring	01	.01	.00	.00	50		
Summer	02	02	.00	.01	49	51	
Firm controls							
Local SME ^d	.07	.04	.05	.06	.02	02	.00
Industry e	_	_	_	_	_	_	_

N = 3415-3422. Pairwise deletion. ^a Speed to decision = number of days; reverse scored so that a positive correlation indicates a faster speed to decision. ^b Past the validity tests as a reflective construct; reflects an overall construct that is comprised of the following EOL components: risk, creative, optimistic, reward, innovative, and proactive. ^c Failed the validity tests as a reflective construct; analysis is performed on each individual COL component. ^d Local SME is operationalized as Scottish venture with up to 250 employees. ^e Ventures represented a total of 34 industry sectors; industry descriptive statistics are provided in Appendix A. EOL = Entrepreneurial-oriented language. COL = Cognitive-oriented language. LIWC = Linguistic Inquiry and Word Count. SME = Small and medium sized enterprise. Proposal accepted (1 = yes; 0 = no). Local SME (1 = yes; 0 = no).

p < .01; correlations of $r \ge |.045|$.

p < .05; correlations greater than $r \ge |.034|$.

	Control Va	riables Only	Hypothesi	s Testing
	Mod Speed to decision ^a Coefficient (SE) [95% CI]	el 1 ^d <u>Proposal accepted</u> Coefficient (SE) [95% CI]	Mod Speed to decision ^a Coefficient (SE) [95% CI]	el 2 <u>Proposal accepted</u> Coefficient (SE) [95% CI]
Local SME	.10** (.03) [.049, .151]	.10** (.02) [.054, .144]	.08** (.03) [.032, .131]	.05** (.02) [.021, .078]
Number of words	.25** (.02) [.216, .289]	.08** (.01) [.060, .106]	.16** (.02) [.126, .197]	04* (.02) [075,010]
Positive	.11** (.02) [.077, .143]	02 (.02) [061, .028]	.09** (.02) [.050, .126]	07** (.02) [112,030]
Negative ^b	04* (.02) [084,004]	03 (.02) [067, .004]	04 (.02) [073, .004]	01 (.01) [036, .017]
Female ^b	.02 (.01) [007, .043]	02 (.02) [057, .009]	.02 (.01) [006, .044]	03 (.02) [066, .000]
Male ^b	.03 (.02) [004, .054]	01 (.02) [038, .026]	.02 (.02) [008, .051]	02 (.01) [046, .008]
Fall °	.01 (.02) [023, .050]	.00 (.02) [032, .041]	.00 (.02) [026, .036]	00 (.02) [031, .027]
Spring ^c	03 (.02) [075, .019]	04* (.02) [069, .008]	03 (.02) [075, .017]	02 (.01) [050 .001]
Insight			08** (.02) [123,042]	
Causation			.07** (.02) [.025, .115]	
Discrepancy			03 (.02) [058, .003]	
Tentative			.00 (.02) [039, .044]	
Certainty			.03 (.02) [009, .066]	
Differentiation			.04 (.03) [021, .104]	
EOL			.07** (.02) [.028, .114]	
Speed to decision				.50** (.02) [.460, .538]
$\frac{R^2}{\Delta R^2}$.12**	.02**	.13** .01	.24**
CFI SRMR RMSEA [95% CI] χ^2 (df)	.1 000] 000. .000	00 00 00, .000] 0(0)	.9 .0 .04 [.02 39.5	8 2 6, 048] 0(7)

TABLE 2 Regression Results in Mplus 8.7

N = 3415. *Listwise deletion*. Standardized coefficients reported. Observations nested within 34 industry clusters. Industry controlled using the *Type* = *Complex* function with *Cluster* = Industry (Muthen & Muthen, 1998-2021). ^a Natural log transformed variable. ^b Inverse hyperbolic sine transformed variable. ^c Dummy variable representing academic season the proposal was opened (summer is reference category). ^d Saturated (just-identified) model. Proposal accepted (1 = yes; 0 = no). Local SME (1 = yes; 0 = no). *p < .05

** p < .00

FIGURE 1 Conceptual Model



APPENDICES

APPENDIX A: Industry Categories

TABLE A1 Proposal Accepted and Days to Decision by Industry

		Proposal acce	epted			
		(1 = yes; 0 =	no)	Num	ber of days to	decision ^a
			Standard			Standard
Industry	N	Mean	Deviation	N	Mean	Deviation
1	31	0.23	0.43	31	1011.65	1173.69
2	48	0.25	0.44	48	969.90	1041.52
3	39	0.44	0.50	39	473.92	505.14
4	14	0.43	0.51	14	621.00	991.32
5	90	0.31	0.47	90	1127.63	1260.12
6	178	0.28	0.45	178	1341.90	1280.54
7	9	0.33	0.50	9	404.56	505.71
8	81	0.38	0.49	80	658.24	816.28
9	42	0.50	0.51	42	584.98	759.65
10	65	0.51	0.50	65	566.34	812.64
11	132	0.36	0.48	132	525.61	688.81
12	86	0.41	0.49	86	574.48	777.44
13	303	0.39	0.49	303	916.01	1176.27
14	121	0.38	0.49	121	1069.88	1187.04
15	210	0.32	0.47	210	926.16	1085.69
16	372	0.33	0.47	372	1082.84	1260.70
17	68	0.40	0.49	68	557.60	840.51
18	26	0.38	0.50	26	857.96	1003.25
19	534	0.41	0.49	534	694.81	920.27
20	20	0.40	0.50	20	791.55	1176.35
21	7	0.43	0.54	7	1189.29	1597.32
22	49	0.51	0.51	49	602.08	806.00
23	279	0.29	0.45	278	1107.29	1263.92
24	9	0.33	0.50	9	763.33	1102.26
25	13	0.31	0.48	13	1007.23	811.99
26	56	0.52	0.50	56	578.38	825.25
27	13	0.69	0.48	13	282.31	347.65
28	1	1.00	-	1	169.00	-
29	139	0.38	0.49	139	501.14	611.39
30	165	0.46	0.50	165	495.88	719.84
31	51	0.35	0.48	51	791.51	1022.66
32	146	0.41	0.49	146	582.02	824.83
33	19	0.37	0.50	18	813.33	1157.52
34	2	0.00	0.00	2	1557.50	1986.26

Key for industry names provided in Table A2. Additional statistics by industry available from the authors. ^a Number of days to decision is reverse coded in the main analyses to assess speed to decision.

Industry 1	Academic	Industry 18	FinTech
Industry 2	Aerospace, Defense and Marine	Industry 19	Food and Drink
Industry 3	Agriculture	Industry 20	Forest Industries and Timber
Industry 4	Aquaculture	Industry 21	Funding Body/Research Council
Industry 5	Business Advice	Industry 22	HR, Recruitment, Training and Team Development
Industry 6	Chemical Sciences	Industry 23	Life Sciences
Industry 7	Commercialization	Industry 24	Marketing and PR
Industry 8	Construction	Industry 25	Media
Industry 9	Creative Ind. (Advertising and Publishing)	Industry 26	Medical Devices
Industry 10	Creative Ind. (Architecture and Design)	Industry 27	Professional Services (Accountants, Banks, Insurance, Legal, Estate Agents etc.)
Industry 11	Creative Ind. (Fashion, Crafts and Arts)	Industry 28	Public Sector
Industry 12	Creative Ind. (Film, TV, Radio, Performing Arts and Music)	Industry 29	Social Enterprise and Third Sector
Industry 13	Creative Ind. (Software and Comp. Serv.)	Industry 30	Sport and Leisure
Industry 14	Electronics	Industry 31	Textiles
Industry 15	Energy	Industry 32	Tourism
Industry 16	Engineering	Industry 33	Transport and Logistics
Industry 17	Environmental	Industry 34	Unknown

TABLE A2 Industry Key for Table A1

APPENDIX B: Results Validating Independent Variables (EOL and COL)

	Factor loadings				
Item	1	2	3		
Tentative	.858				
Discrepancy	.700				
Differentiation	.668	.470			
Causation		.743			
Insight		729			
Certainty			.990		

TABLE B1 Split Sample Exploratory Factor Analyses (EFA) of COL

N = 1711. EFA of Subsample 1. Principal component analysis, Promax rotation with Kaiser normalization. Results of the split sample EFA suggest that the items do not reflect a higher order construct of COL. COL = cognitive-oriented language.

TABLE B2 Split Sample Confirmatory Factor Analysis (CFA) of COL in Mplus 8.7

Item	Coefficient (λ)	SE	<i>p</i> -value
Truck time	1 200	227	< 001
Tentative	1.298	.227	<.001
Discrepancy	.280	.081	.001
Differentiation	.352	.064	<.001
Causation	080	.020	<.001
Insight	.162	.048	.001
Certainty	133	.021	<.001

N = 1711. CFA of Subsample 2. Results of the split sample CFA suggest that the items do not reflect a higher order construct of COL. COL = cognitive-oriented language.

Item	Cronbach's Alpha (α)	Cronbach's Alpha (α) if item deleted
COL	.227	-
Tentative	-	.012
Discrepancy	-	.086
Differentiation	-	.013
Causation	-	.428
Insight	-	.335
Certainty	-	.244

TABLE B3 Reliability Analysis of COL as a Reflective Construct

N = 3422. Reliability analysis of full sample. Results of reliability analysis of COL suggest that the items do not reflect a higher order construct of COL. COL = cognitive-oriented language.

	Factor loadings		
Item	1	2	
Risk	.696		
Creative	.864		
Optimistic	.847		
Reward	.967		
Innovative	.679		
Proactive	.964		
Uncertainty		.975	

TABLE B4 Split Sample Exploratory Factor Analyses (EFA) of EOL

N = 1711. EFA of Subsample 1. Principal component analysis, Promax rotation with Kaiser normalization. Results of the split sample EFA suggest that *Uncertainty* does not reflect a higher order construct that is consistent with all other EOL items. EOL = entrepreneurial-oriented language.

TABLE B5 Split Sample Confirmatory Factor Analysis (CFA) of EOL in Mplus 8.7

Item	Coefficient (λ)	SE	<i>p</i> -value
D' 1	644	0.40	< 0.01
KISK	.644	.040	<.001
Creative	.850	.019	<.001
Optimistic	.832	.017	<.001
Reward	.969	.006	<.001
Innovative	.686	.035	<.001
Proactive	.902	.011	<.001

N = 1711. CFA of Subsample 2. Results of the split sample CFA suggest that the items reflect a higher order construct of EOL. *Uncertainty* excluded from EOL construct based on split sample EFA. EOL = entrepreneurial-oriented language.

Item	Cronbach's Alpha (a)	Cronbach's Alpha (α) if item deleted
EOL	.919	-
Risk	-	.922
Creative	-	.894
Optimistic	-	.907
Reward	-	.882
Innovative	-	.920
Proactive	-	.892

TABLE B6 Reliability Analysis of EOL as a Reflective Construct

N = 3422. CFA of Subsample 2. Results of reliability analysis of EOL suggest that the items do not reflect a higher order construct of EOL. *Uncertainty* excluded from EOL construct based on split sample EFA. EOL = entrepreneurial-oriented language.

APPENDIX C: Bootstrap Analysis and Robustness Tests

Bootstrap Analysis

We performed a bootstrap analysis of the hypothesized associations (500 random resampling with replacement) to provide a more rigorous test of the findings (Williams & Shepherd, 2016). We assessed the bootstrapped associations based on their 95% confidence intervals (CIs). Associations that do not include 0 in their 95% CI support the conclusion that the associations are significantly different from 0 (Lau & Cheung, 2012; MacKinnon et al., 2004). All significant associations found in the structural equation models (Table 2) did not include 0 in their bootstrapped 95% CIs. Thus, the bootstrapping results are consistent with the main results.

Robustness Tests

We performed a series of robustness tests to further examine the findings. Table C1 displays the results of these checks. First, to examine the possible effects of spurious outliers we winsorized *speed to decision* (Sun & Im, 2015) by replacing values that were greater than three standard deviations above the mean with the highest value that was within the three standard deviations cutoff. We then reran the model that examined Hypotheses 1 through 3. As displayed in Model 1 of Table C1 ($\chi^2_{(df)} = 39.43_{(7)}$, RMSEA = 0.04, CFI = 0.98, SRMR = 0.02), *insight* showed a negative association with *speed to decision* ($\beta = .07$, p < .01). Moreover, EOL showed a positive association with *speed to decision* ($\beta = .07$, p < .01), and *speed to decision* showed a positive association with *speed to decision* ($\beta = .07$, p < .01).

Second, we reran the model without control variables to examine the extent to which they might be influencing the results (e.g., multicollinearity). As displayed in Model 2 of Table C1 $(\chi^2_{(df)} = 52.75_{(7)}, \text{RMSEA} = 0.04, \text{ CFI} = 0.96, \text{ SRMR} = 0.03), insight (\beta = -.14, p < .01) and discrepancy (\beta = -.04, p < .01) showed negative associations with speed to decision, whereas$

causation ($\beta = .12, p < .01$), certainty ($\beta = .05, p < .05$), and differentiation ($\beta = .08, p < .05$) showed positive associations with speed to decision. The association between tentative and speed to decision was not significant. Moreover, EOL showed a positive association with speed to decision ($\beta = .14, p < .01$), and speed to decision showed a positive association with proposal accepted ($\beta = .48, p < .01$).

Lastly, we ran two direct models (i.e., non-mediation models) on *speed to decision* excluding COL components and the EOL construct from respective models. As shown in Model 3 of Table C1 ($\chi^2_{(df)} = 0.00_{(0)}$, RMSEA = 0.00, CFI = 1.00, SRMR = 0.00), when excluding the COL components, the results continued to show a positive association between EOL and *speed to decision* ($\beta = .08, p < .01$). As shown in Model 4 of Table C1 ($\chi^2_{(df)} = 0.00_{(0)}$, RMSEA = 0.00, CFI = 1.00, SRMR = 0.00), when excluding the EOL construct, *insight* ($\beta = -.09, p < .01$) and *discrepancy* ($\beta = -.03, p < .05$) showed negative associations with *speed to decision*. The associations of *tentative, certainty*, and *differentiation* with *speed to decision* were not significant.

	Winsorized D	ecision Speed	Without Controls		Speed to Decision Only	
	Mod	el 1	Moo	del 2	Model 3	Model 4
	Speed to	Proposal	Speed to	Proposal	Speed to	Speed to
	decision ^a	accepted	decision a	accepted	decision ^a	decision a
	Coefficient (SE) [95% CI]					
Controls entered	Yes	Yes	No	No	Yes	Yes
Insight	08** (.02) [123,043]		14** (.03) [185,094]		-	09** (.02) [127,045]
Causation	.07** (.02)		.12** (.03)		-	.07** (.02)
	[.025, .115]		[.075, .172]		-	[.023, .114]
Discrepancy	03 (.02)		04** (.02)		-	03* (.02)
,	[058, .003]		[067,009]		-	[064,004]
Tentative	.00 (.02)		04 (.02)		-	.00 (.02)
	[039, .044]		[085, .006]		-	[040, .044]
Certainty	.03 (.02)		.05* (.02)		-	.03 (.02)
	[009, .066]		[.012, .094]		-	[005, .069]
Differentiation	.04 (.03)		.08* (.03)		-	.04 (.03)
	[021, .104]		[.015, .141]		-	[018, .106]
EOL	.07** (.02)		.14** (.03)		.08** (.02)	
	[.028, .114]		[.090, .187]		[.035, .122]	
Decision speed ^a		.50** (.02)		.48** (.02)		
		[.460, .538]		[.443, .509]		
CFI	.9	8	.9	96	1.00	1.00
SRMR	.0	2	.()3	.00	.00
RMSEA [95% CI] χ^2 (df)	.04 [.020 39.4	6, .048] 3(7)	.04 [.03 52.7	3, .055] 5 (7)	.00 [.000, .000] .00(0)	.00 [.000, .000] .00(0)

TABLE C1 Robustness Check of Direct and Mediation Effects

 $\overline{N} = 3415$. *Listwise deletion*. Standardized coefficients reported. Observations nested within 34 industry clusters. Industry controlled using the *Type* = *Complex* function with *Cluster* = Industry (Muthen & Muthen, 1998-2021). Variables in interaction terms were grand mean centered. ^a Natural log transformed variables. *p < 05

p < .05** p < .01

APPENDIX D: Post Hoc Analysis

We do not assume or theorize direct associations between the X and Y variables in our $X \rightarrow M \rightarrow Y$ path model. We theorize that EOL/COL (X) is connected to Decision Outcome (Y) through theoretical mechanisms related to decision-making heuristics and Decision Speed (M). Our theorizing implies no connection between EOL/COL and Decision Outcome without considering these theoretical mechanisms. As such, our model is consistent with "indirect effects hypotheses" that exclude direct effects between the X and Y variables (Mathieu & Taylor, 2006). That said, we acknowledge contentions in the literature about the inclusion/exclusion of a direct link between X and Y variables in an $X \rightarrow M \rightarrow Y$ path model. As such, we performed a "post hoc" analysis to assess whether a direct link between EOL/COL and Decision Outcome should be included in our proposed model.

Post Hoc Analysis: Alternative Mediation Model (i.e., direct link included)

To examine the possibility of partial or full mediation we ran a model with a direct link between EOL, Insight, and Causation (X variables) with Decision Outcome (Y variable) as these were the significant indirect paths in our theorized model. Adding the direct paths had no influence on the indirect effects via the X \rightarrow M path (EOL \rightarrow Speed to Decision, $\beta = .07$, p = .001; Insight \rightarrow Speed to Decision, $\beta = .07$, p = .002) or the M \rightarrow Y path (Decision Speed \rightarrow Decision Outcome, $\beta = .51$, p = .000). The results did, however, show a significant negative direct association between two of the X \rightarrow Y direct paths (EOL \rightarrow Decision Outcome, $\beta = .05$, p = .005; Insight \rightarrow Decision Outcome, $\beta = .05$, p = .005). The other X \rightarrow Y path was not significant (Causation \rightarrow Decision Outcome, $\beta = .02$, p = .097). The results of this model suggest potential direct associations between X and Y variables, which could indicate a partial mediation model. To assess the possibility that a partial mediation model is more appropriate than an indirect effects model we ran the following robustness tests.

Robustness Test 1. We swapped Decision Speed with Decision Outcome, placing Decision Outcome as the mediator and Decision Speed as the dependent variable. The results showed no significant associations of EOL or COL facets with Decision Outcome. As such, this model suggests no direct link between the X and Y variables of our hypothesized model.

Robustness Test 2. We set both Decision Speed and Decision Outcome as dependent variables, allowing the two to correlate. Like the previous test, the results showed no significant associations of EOL or COL facets with Decision Outcome, suggesting no direct link between the X and Y variables of our hypothesized model. There were, however, significant associations for Decision Speed with EOL ($\beta = .07$, p = .002), Insight ($\beta = -.08$, p = .000), and Causation ($\beta = .07$, p = .001), thus providing support for significant associations between the X and M variables of our hypothesized model. Moreover, there was a significant correlation between Decision Speed and Decision Outcome (r = .60, p = .000) thus supporting an association between the M and Y variables of our hypothesized model.

Robustness Test 3. We set both Decision Speed and Decision Outcome as dependent variables, not allowing them to correlate. Like the two previous tests, the results showed no significant associations of EOL or COL facets with Decision Outcome. There was again, however, a significant association for Decision Speed with EOL ($\beta = .07$, p = .001), Insight ($\beta = -.08$, p = .000), and Causation ($\beta = .07$, p = .001).

Altogether, a partial mediation model failed these robustness tests thus providing weak evidence of a true direct effect between the X and Y variables. Moreover, the indirect effects showed little to no change and are thus not dependent on the inclusion or exclusion of a direct effect. Altogether, both the theorizing used to support our proposed model, and the empirical evidence provided by the post hoc analysis support an indirect effects model over a partial mediation model.

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