

UNVEILING THE NATURE OF BIG DATA ANALYTICS CAPABILITIES TRUST AND THE MODERATING ROLE OF ENVIRONMENTAL HOSTILITY

To realize a data-driven transition, firms must evolve into more collaborative and democratic entities. This requires cultivating organizational trust and understanding its effects on developing the tangible, intangible, and human resources relating to big data analytics capability (BDAC). Despite the relevance of the topic, empirical evidence on the impact of organizational trust on BDAC is lacking. This paper explores the effects of organizational trust on various dimensions of BDAC and analyzes the moderating role of environmental hostility. Our research reveals the contingency-dependent nature of trust in developing BDAC, as its effects become positive when entrepreneurs perceive increasing environmental hostility. To fully leverage a data-driven transition in hostile environments, managers should focus on achieving higher organizational trust to enable a data-driven culture, improve technical and managerial skills, and empower employees.

MANAGEMENT//ORGANIZATIONAL TRUST//BIG DATA ANALYTICS//ENVIRONMENTAL HOSTILITY//SMEs



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INTRODUCTION

Big data represents a disruptive paradigm shift for businesses (Chauhan et al., 2022; George et al., 2014; Ekbja et al., 2015). According to McAfee and Brynjolfsson (2012), firms that anchor their activities on data show productivity rates and profitability that are 5% or 6% higher than their counterparts. Data-driven firms are business organizations that build tools, abilities, and culture on data (Anderson, 2015; Persaud and Zare, 2024). To leverage the potential of data effectively, the various roles in these firms are often structured into multiple teams, each possessing complementary competencies. The culture of data-driven organizations is goal-first, inquisitive, learning-oriented, and iterative (Anderson, 2015). This cultural footprint is reflected in information exchanges and internal dialogues that extend beyond traditional

business boundaries, which are often perceived as silos (Kitchens et al., 2018). Therefore, data-driven organizations are collaborative and democratic since teams are conceived, from top-down and bottom-up, to share knowledge and information by providing broad access to data to all their members.

Typically, an organization can unleash its potential through information exchange and close cooperation among its members, functional areas, or business units. To achieve this, cultivating organizational trust (OT) is key (Castaldo et al., 2010; Guinot et al., 2016; Kayabay et al., 2022). While technical solutions like big data analytics and artificial intelligence (AI) garner considerable attention (Sullivan and Wamba, 2024), we must recognize that organizations are fundamentally about people (Huynh et al., 2023; Korherr and Kanbach, 2023; Mikalef et al., 2019a). How individuals collaborate and work together impacts organizational performance. Boosting competitiveness in the big data era hinges on addressing people-centric issues rather than solely relying on new technology implementations (Forbes et al., 2023).

OT is the fundamental foundation of dynamic capabilities and big data analytics capability (BDAC) (Fainshmidt and Frazier, 2017). Indeed, dynamic capabilities depend on collective learning and coordinated efforts by organization members, both influenced by the organization's social climate. This in turn shapes patterns in attitudes, behaviors, and interpersonal relationships among colleagues. As a result, this study argues that OT can directly impact the development of BDAC by facilitating information processing and knowledge management, improving the collaborative dynamics at an organizational level, boosting responsiveness, and stimulating continuous learning mechanisms (Nyamrunda and Freeman, 2021; Pattanayak et al., 2024; Salancik and Pfeffer, 1978).

Despite the prominent role of OT in data-driven organizations, no empirical evidence reveals what the actual impact of OT is with regard to the multiple dimensions of BDAC and how each one develops (Fainshmidt and Frazier, 2017; Grover et al., 2018; Gupta and George, 2016; Mikalef et al., 2019a). BDAC

is a multidimensional construct that includes all organizational resources relevant to the transition toward data-driven. These dimensions refer to tangible (e.g., data, time, financial resources), intangible (e.g., data-driven culture and organizational learning), and human resources (e.g., technical and managerial skills). Understanding the influence of OT on BDAC development can further our comprehension of the antecedents that successfully drive a firm's adoption of the big data paradigm. Previous literature has made limited progress in identifying said antecedents, leaving a major research gap (Huynh et al., 2023).

To fill this gap, our paper aims to analyze the relationships between OT and BDAC dimensions to help unveil the complexity of BDAC and discover its intrinsic nature. Unpacking a construct means extracting it from its "black box" and contributing to its theoretical development while providing more specific practical takeaways.

This research also considers environmental hostility (EH) as a moderator, focusing on its interplay with OT. By doing this, the present paper addresses the call for further studies (Huynh et al., 2023) to examine the influence of environmental factors on the development of BDAC (Mikalef et al., 2019a). Investigating EH as a moderator of BDAC can also help reinforce our methodological rigor (Huynh et al., 2023), as it allows us to identify boundary conditions and significant contexts, deriving more precise insights into the relationship between OT and BDAC. More solid OT equips firms with a greater capacity to accomplish organizational changes (van Dam et al., 2008), improving the ability to share information among members (Oh, 2019). For this reason, OT may offer distinct advantages to firms operating in hostile environments where information proliferation is heightened.

Here, we argue that EH can compel firms to adopt data-centric strategies to manage spiraling complexity and uncertainty (Teece et al., 2016). The perception of EH can influence the collaborative efforts of business teams (Breugst et al., 2020) and determine organizational changes to cope with new environmental conditions (Hitt et al., 2020), representing a stimulus to undertake strategic change

by developing BDAC. Therefore, the interaction between OT and EH could be constructive as far as BDAC development. Taking stock of the previous research gaps and drawing on the dynamic capabilities view (Teece, 2007; Teece et al., 2016), this paper answers the following research questions: **What is the relationship between OT and BDAC? What is the role played by EH in this linkage?**

To accomplish the research aims described above, this study applies partial least square-path modeling (PLS-PM) on a sample of 200 Italian SMEs. Our findings reveal the contingency-dependent nature of trust with regard to BDAC development, as the effects of trust become positive when entrepreneurs perceive rising EH. The results indicate that, if there are no external triggers, the effectiveness of OT in advancing a data-driven transformation diminishes.

Our paper contributes to the existing literature by addressing two significant research gaps. First, we enrich the research on trust and big data by empirically examining the relationship between OT and the multidimensional construct BDAC. Our work enhances our knowledge of the antecedents that drive a successful transition toward the big data paradigm. Second, this study incorporates EH as a moderating factor, responding to calls for further investigation into the influence of environmental conditions on BDAC development. By exploring the interplay between OT and EH, this research provides insights into the boundary conditions and contextual factors that shape the relationship between OT and BDAC. Third, this paper contributes to the context-specific literature on big data in SMEs, demonstrating that BDAC is inherently trust-based and contingency-dependent in such contexts.

Improving our knowledge on this topic can have relevant implications for business practice. In a hostile environment, OT is a driver that facilitates the development of multiple BDAC dimensions, including organizational learning, data-driven culture, technical and managerial skills, and data management. Therefore, executives should monitor the level of OT and invest in building social relationships and a stronger sense of community (Gratton and Erickson, 2007). Firms could capitalize on the interplay between

OT and EH to enable inclusive, flowing data-driven decisional processes, avoiding the erratic choices that decision-makers may make when they challenge growing environmental complexity (Mitchell et al., 2011).

LITERATURE REVIEW

Organizational trust (OT)

Trust indicates one's expectation that a person who is honest, benevolent, and competent will perform future actions that are beneficial for the trustor in situations of perceived risk and vulnerability (Castaldo et al., 2010). In this condition, trustors expose themselves to vulnerability by trusting; trust is the "willingness to take risks" (Schoorman et al., 2007, pp. 346). Specifically, OT is the trustor's expectation (e.g., employee, manager, etc.) that a workmate will perform an activity that brings organizational benefits in situations of interdependence, where the completion of a task depends wholly or partly on the action of that workmate (Huff and Kelley, 2003; Kramer and Lewicki, 2010). OT can embrace multiple hierarchical levels and individuals at the same level. Specifically, lateral trust indicates the trust between workmates with similar positions in the organization. Instead, vertical trust involves the relationships between workers and their superiors or subordinates (McCauley and Kuhnert, 1992).

OT is a context-specific concept. In other words, every organizational context gives rise to unique trust-based relationships among the organization's members. For example, the power relationships and the information asymmetry between supervisors and subordinates generate different degrees of trust in organizations (Schoorman et al., 2007). What's more, breakdowns in trust can have dangerous consequences (Gillespie and Dietz, 2009; Kramer and Lewicki, 2010), so organizations should nurture this nonmaterial factor to avoid default and maximize its potential. Also, the concept of OT extends beyond interpersonal trust to include trust in technology, such as AI (Glikson and Woolley, 2020). In fact, since

AI will increasingly shape future workplaces, human trust in technology becomes crucial to developing BDAC effectively.

Fainshmidt and Frazier (2017) define “trust as a social foundation of dynamic capabilities” (p. 550). The same authors highlight that such capabilities “rely on collective learning and coordinated effort by organization members, the organization’s social climate, which shapes patterns in attitudes, behaviors, and interpersonal relationships among organizational members” (p. 550). They find that trust directly influences the development of these dynamic capabilities, enabling social information processing and social exchange, and affects how the organization’s members act and think (Hellriegel and Slocum, 1974; Salancik and Pfeffer, 1978). Trust can enhance relational dynamic capabilities by fostering responsiveness and ensuring reliable communication between business actors (Nyamrunda and Freeman, 2021; Pattanayak et al., 2024). By building trust, firms strengthen their dynamic capabilities of knowledge sharing and new resource combinations, culminating in the increase of a firm’s absorptive capacity (Pütz et al., 2023). When colleagues trust one another, they are more likely to share information and collaborate effectively. This enhanced trust fosters an organizational environment where employees feel safe sharing their thoughts and vulnerabilities, resulting in more open, transparent communication (Pattanayak et al., 2024). Also, building trust makes it easier to capture capabilities by enabling cooperation, engagement, and minimizing conflicts (Tabaklar et al., 2021).

Big data analytics capability (BDAC)

To transition into data-driven organizations, firms need to shift their decision-making style from intuition-centered to data-centric (McAfee and Brynjolfsson, 2012; Tabesh et al., 2019). Big data opens paths to new strategizing since data-driven organizations tend to take data-led information as the primary source of viable knowledge (van Rijmenam et al., 2019). However, the realization of big data potential hinges on a more complex architecture of elements at the organizational level. Academic

literature refers to the multidimensional concept of BDAC to indicate the firm’s ability to exploit big data and generate strategic insights (Grover et al., 2018). In fact, BDAC improves firms’ strategies by leveraging new information, amplifying the synergies between business areas, and making it possible to seize new business opportunities (Aker et al., 2016). In addition, by leveraging BDAC, firms can address market changes and customer needs, optimize their internal operations, and innovate their business models (Ciacci and Penco, 2023; Dubey et al., 2020; Kitchens et al., 2018; Ur Rehman et al., 2016). BDAC facilitates environmental scanning as well, which firms use to identify opportunities for new productions (Duan et al., 2020; Sheng et al., 2017). BDAC also enables the development of dynamic capabilities (e.g., agility, Mikalef et al., 2019a; Sivarajah et al., 2017) and reduces uncertainty by extracting meaning from data to improve strategic decision-making (Chen et al., 2015).

Gupta and George (2016) identify three BDAC components, i.e., tangible, intangible, and human resources. Tangible resources involve the technological architecture adopted to integrate, store, process, analyze, and visualize data, the amount of data at disposal, and basic resources (e.g., money to invest, time) (Dubey et al., 2020; Gupta and George, 2016). Since firms can buy tangible resources on the market, they do not represent potential sources of competitive advantage. Instead, intangible resources, which are critical for the success of an organization’s BDAC, represent differentiating factors over rivals. Intangible resources refer to a data-driven organizational culture (McAfee and Brynjolfsson, 2012), allowing firms to collect, manage, share, and exploit by data-driven decision-making, and organizational learning. This process consists of exploring, storing, sharing, and applying knowledge (Chen et al., 2015). Lastly, human resources represent the technical, managerial, and relational competencies surrounding employees who work in a data-driven organization (Anderson, 2015; Wamba et al., 2017). The interaction between these elements helps create a differentiation factor (Sivarajah et al., 2017).

Because BDAC is the sum of tangible, human, and intangible resources, it represents a distinctive aptitude for creating innovative business models (Ciacci and Penco, 2023).

Environmental hostility (EH)

Shifting from intuitive to data-centric decision-making paradigms can enhance the firm's ability to effectively address new environmental conditions and windows of opportunity by improving responsiveness, reducing cognitive biases, and providing timely strategic insights (Grover et al., 2018; Sullivan and Wamba, 2024). This ability is crucial to stay competitive in turbulent, unstable business environments. Therefore, the perception of environmental complexity and unpredictability can lead firms to undertake strategic changes to develop new dynamic capabilities to respond to changing external conditions (Clauss et al., 2021; Teece, 2007). The literature demonstrates that environmental turbulence is a crucial contingent variable in the dynamic capabilities view (Chen et al., 2015; Kreiser et al., 2020; Michaelis et al., 2021).

Our paper deals with the concept of EH, a specific form of turbulence centering on the action of competitive external forces that threaten firms (Breugst et al., 2020). Precisely, EH indicates "the degree of threat to the firm posed by the multifacetedness, vigor and intensity of the competition and the downswings and upswings of the firm's principal industry" (Miller and Friesen, 1983, p. 222). These threats include characteristics of the industry, competition, customers, and markets (Green et al., 2008), such as the firms' failure rate, competitive intensity, customer loyalty, and profit margins. Hostile environments are marked by fluid market structures, globally dispersed expertise and technologies, and a constant search for innovation (Teece, 2014). As a result, environmental hostility forces firms to break away from established routines and engage in continuous learning to manage new layers of complexity and uncertainty, which improves their chances of survival and success in these hostile conditions (Teece et al., 2016). All these exogenous factors undermine the firms'

ability to control the fate of their competitiveness (Michaelis et al., 2021). Since entrepreneurs in the same industry may perceive EH differently (Tang and Hull, 2012), it can be viewed either as an opportunity or a threat. Indeed, while EH poses risks to business competitiveness, it also serves as a catalyst for innovation, spurring the firm to adopt new organizational paradigms (Hitt et al., 2020; Mikalef et al., 2019a).

HYPOTHESES DEVELOPMENT

The relationship between OT and BDAC

Higher OT can result in more data flowing between the different functional areas (Anderson, 2015) due to managers' belief that their workmates can derive valuable information from the volume of data (Kayabay et al., 2022; Levin and Cross, 2004). Therefore, data-driven firms may leverage their OT by acquiring more data to create new knowledge (Barton and Court, 2012), as knowledge is more manageable and more easily transferable when trust-based ties are stronger (Levin and Cross, 2004). Literature shows that higher levels of OT can trigger the propensity to innovate processes (Ellonen et al., 2008). OT also enhances investment decisions by instilling confidence in the organization's ability to effectively deploy new tools, competencies, and knowledge, with the expectation of rewarding outcomes. Therefore, since trust is associated with expectation (Castaldo et al., 2010), OT may stimulate managers to invest more resources when they believe that this would allow workmates to improve their attitudes and the competencies they need to do their jobs. Finally, this inclination to invest resources in developing BDAC may lead to improving the technological infrastructure (Ellonen et al., 2008).

In addition, OT may positively impact the human dimension of BDAC. The success of managers' skills depends on their ability to coordinate, share information with workmates, and deal with new knowledge (Gupta and George, 2016; Mikalef et al., 2019a). Therefore, such skills

may benefit from a context with more trust among workmates and more willingness to work together. At the same time, higher OT leads superiors to democratize the internal decisional process, tasking their subordinates to develop the analytical skills they need (Anderson, 2015). In addition, a firm with higher OT may offer more training programs to employees to hone their analytical competencies (Tzafrir, 2005). Finally, technical skills may improve thanks to constant internal dialogue and enhanced collaboration (Braganza et al., 2017).

By prompting investments in employee training, OT fosters a data-driven culture (Mikalef et al., 2019a). Specifically, cultivating such a culture means delegating responsibilities to employees with the appropriate skills to extract strategic insights from data (Anderson, 2015; Kayabay et al., 2022). Higher levels of OT reinforce this dynamic (Liden et al., 1993). In addition, a data-driven culture is an open-minded environment where relationships are crucial. For instance, data-driven decisions are supported by constant interactions among data analysts and decision-makers. Making decisions based on data analytics is an iterative process informed by the coordinated integration of complementary forms of knowledge (Hindle and Vidgen, 2018). OT may also positively affect the organization's learning (Guinot et al., 2013; Guinot et al., 2016), encouraging people to share, interact, and work as a team (Mayer et al., 1995). In other words, higher OT may benefit organizational learning by improving information transmission and knowledge creation (Oh, 2019). Therefore, we formulate the following hypotheses:

H1. OT significantly and positively affects the data (H1a), basic resources (H1b), technology (H1c), managerial skills (H1d), technical skills (H1e), data-driven culture (H1f), and organizational learning (H1g) dimensions of BDAC.

The moderating effect of EH in the relationship between OT and BDAC

When EH is higher, firms are more likely to undertake strategic change to address the environmental conditions (Breugst et al., 2020; Clauss et al., 2021; Teece, 2007), facilitating a transition from

an intuition-based to a data-centric paradigm. By leveraging superior OT levels, firms can acquire and share larger volumes of data. The widespread dissemination of data facilitated by OT across functional areas leads to better management of information flows and analytics processes. The volume of data proliferating in hostile environments is greater because of the more powerful dynamics surrounding big data creation (George et al., 2014). When the amount of data increases, the need for an adequate technological architecture to store, visualize, and analyze data emerges. By implementing more advanced technologies, firms can process data to reduce environmental complexity and derive more comprehensible insights.

Therefore, the interaction between OT and EH may positively affect the propensity to prioritize investing in big data projects and implementing new technologies. In hostile environments, decision-makers need a strategic tool to facilitate the decisional processes in the face of enhanced complexity (Breugst et al., 2020; Mitchell et al., 2011). When EH is more intense and the need for agile, and flexible decisional tools becomes more urgent, higher OT may lead firms to invest more basic resources in BDAC, under the assumption that workmates will contribute to generating positive returns from the investment.

Managerial skills depend on managers' ability to cooperate, share information, and deal with new knowledge, i.e., the mutual trust among managers and workmates (Castaldo et al., 2010; Jones and George, 1998; McAllister, 1995). Trust may be even more pronounced as EH grows. Thompson (1967) writes that, under conditions of uncertainty and complexity, mutual trust is a requirement to sustain coordinated actions and adjustments. OT plays a relevant role in enhancing managerial skills in decision-making, particularly in environments that demand swift strategic responses. In addition, OT intensifies the frequency of organizational dialogue, a core aspect of managerial skills. Concerning technical skills, firms need professionals to derive strategic insights from data. As a reaction to EH, superiors may democratize the internal decisional

process by entrusting subordinates possessing adequate skills to enact them to exploit data (Anderson, 2015). Also, higher OT leads to improving employee training to raise their analytical competencies. This is especially the case when EH intensifies, posing new challenges and giving rise to the need to acquire, analyze, and exploit data with greater speed and precision. In other words, EH prompts organizations to invest more resources to train their employees, and OT is the fertile ground where that training can be most effective. Since big data augments the ability to manage risks and make timely decisions (Mikalef et al., 2019a), EH facilitates the progressive development of data-driven mental models, resulting in an enhanced big-data culture.

In conditions of EH, acquiring and analyzing larger volumes of data can lead to the extraction of more relevant knowledge (Urbinati et al., 2019). However, greater EH generates a higher proliferation of information that requires processing. In this regard, OT is crucial in enabling firms to utilize data for assimilating and generating new knowledge. With no OT to serve as a catalyst it may be difficult for firms to activate smooth routines based on information exchange between members while avoiding information overload.

Therefore, we argue that:

H2. EH significantly and positively moderates the relationship between OT and the data (H2a), basic resources (H2b), technology (H2c), managerial skills (H2d), technical skills (H2e), data-driven culture (H2f), and organizational learning (H2g) dimensions of BDAC.

Figure 1 depicts the conceptual model and linkages between the higher-order variables in our study. We posit that OT plays a significant role as an antecedent of dimensions of BDAC, while we expect EH to moderate such relationships positively.

METHODOLOGY

To empirically test the hypotheses, we apply partial least square–path modeling (PLS-PM) and bootstrapping validation on a cross-sectional and

cross-industry sample of 200 Italian SMEs. The PLS method is commonly employed for analyzing causal relationships due to its robustness in handling variables that do not follow a normal distribution (Ciacci and Penco, 2023; Galindo-Martín et al., 2019). Additionally, PLS enhances the predictive accuracy of the analysis, making it a suitable choice for research focused on predictive modeling (Benitez et al., 2020). The units of analysis have been randomly chosen among firms using big data analytics. The respondents are entrepreneurs (9%), members of the owner family engaged in business management (20.9%), and top managers (70.1%). All the respondents are people involved in strategic management with a global understanding of the firm's business model, activities, and processes; 80% are men and 20% are women. Respondents are aged 50–64 (53%), 35–49 (43.5%), and over 65 (3.5%). The firms in our sample belong to different sectors, including manufacturing (55%), trade (24%), services (16.5%), primary industries (2.5%), financial services (1.5), and utilities (0.5%).

Measurement scales

During the preparatory stage of our research, we ran a pilot test with a subsample of 26 respondents to identify potential issues and refine the wording of the questions. In this phase, participants were asked to review and validate the relevance and completeness of the questionnaire items. Their feedback was instrumental in adjusting specific items, enhancing the clarity and reliability of the finalized questionnaire. The constructs are measured through 7-point Likert scales tested and validated in the literature. OT, derived from Huff and Kelley (2003), includes items like, “There is a very high level of trust in this organization,” and “If someone in this organization makes a promise, other individuals within the organization will almost always trust that the person will do their best to keep the promise.” BDAC is measured through the multidimensional scale by Mikalef et al. (2019a). EH is based on the scale compiled by Green et al. (2008), including items like “The failure rate of firms in my industry is high,” “My industry is very risky, such that one bad decision

could easily threaten the viability of my business unit,” and “Low-profit margins are characteristic of my industry.” We performed an exploratory factor analysis on each latent construct to check the robustness of the scales and exclude the items that show a weak correlation to the factor in question.

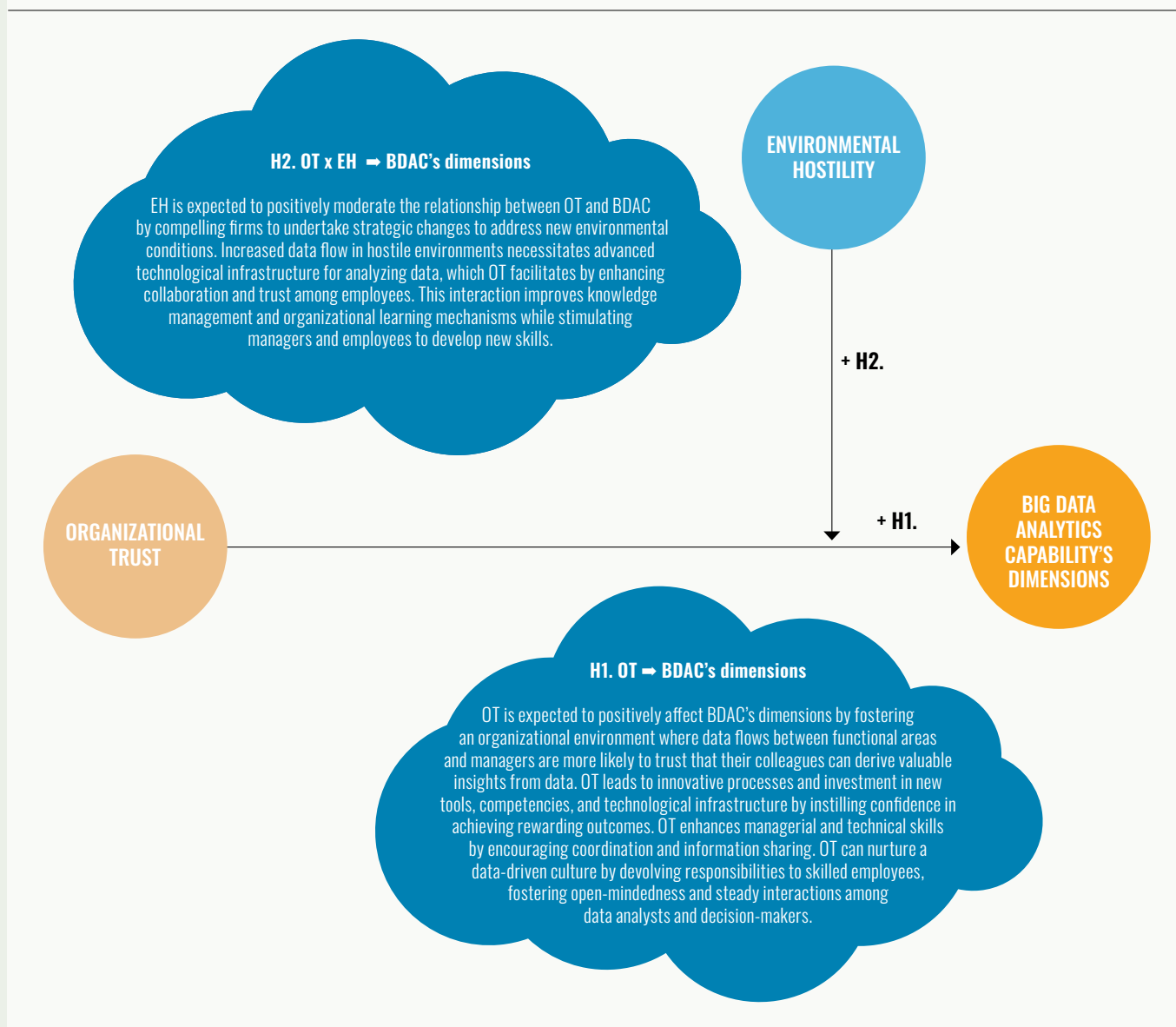
Measurement model

Model validation considers the formative and reflective nature of the constructs (Henseler et al., 2014). Formative construct validity is tested by

checking the adequacy coefficient (R^2) (MacKenzie et al., 2011). For all the constructs, R^2 is higher than the threshold of 0.5. The variance inflation factors (VIF) test does not show multicollinearity problems, as it is lower than 10. Finally, all the weights of the items and the latent constructs are statistically significant (Petter et al., 2007).

In testing the reflective constructs for reliability, Cronbach's alpha reaches the threshold of 0.7. We performed a supplementary test (DG rho) in which all the values were higher than 0.815, supporting

FIGURE 1. CONCEPTUAL MODEL



the internal consistency of the constructs. In addition, the outer loadings are higher than cross-loadings, and AVE exceeds the threshold of 0.5 in all cases, proving an overall good discriminant validity. We conclude that the tests demonstrate the overall robustness of the constructs.

RESULTS

In this study, we run two distinct models. The first model tests the control variables (age and gender) on the dependent variables. The only significant output it provides is the positive effect of age on managerial skills ($\beta = 0.148$; $t\text{-value} = 2.110$). This result highlights the importance of experience in relation to managerial skills (Gupta and George, 2016), a difficult-to-teach, firm-specific competence. In fact, as managers age, they accumulate inimitable knowledge and insights from their interactions and decision-making processes in the firm, sharpening their overall managerial skills. This experiential learning contributes to their ability to effectively deploy resources to optimize processes and identify emerging opportunities (Mannor et al., 2016).

The second model tests the hypotheses (Figure 2). Table 1 summarizes the results of the PLS model and bootstrap validation. Considering the relationships between OT and BDAC dimensions, OT-technology ($\beta = -0.363$; $t\text{-value} = -5.482$) and OT-organizational learning ($\beta = 0.159$; $t\text{-value} = 2.177$; $CI = 0.011, 0.304$) prove to be significant. Moreover, OT seems to negatively influence the adoption of new technologies to exploit big data analytics. Considering the hypotheses of a direct effect of OT on the single dimensions of BDAC, our model only confirms H1g.

When EH acts as a moderator, the relationships become significant and positive ($\beta = 0.427$; $t\text{-value} = 6.442$). More in general, the effect of OT in a hostile environment generates significant increases in resources ($\beta = 0.318$; $t\text{-value} = 4.460$), technology ($\beta = 0.427$; $t\text{-value} = 6.442$), manager skills ($\beta = 0.269$; $t\text{-value} = 3.716$), technical skills ($\beta = 0.209$; $t\text{-value}$

$= 2.884$), data-driven culture ($\beta = 0.221$; $t\text{-value} = 3.025$), and organizational learning ($\beta = 0.124$; $t\text{-value} = 1.695$; $CI = 0.003, 0.301$). This means that OT is a noteworthy antecedent of BDAC in a hostile environment, except for the relationship between OT and the data dimension ($\beta = 0.261$; $t\text{-value} = 3.614$). Instead, bootstrapping does not support the significance of the relationship between OT and data ($CI = -0.198, 0.458$) moderated by EH. In summary, our model validates all moderation hypotheses except for H2a.

DISCUSSION

Our findings indicate that OT enhances BDAC by significantly influencing its constitutive dimensions under the moderating effect of EH. The impact of OT as an antecedent of BDAC is contingent since it depends on EH moderation. In this context, OT lays the groundwork for an organizational environment in which to develop the different dimensions of BDAC.

When there is no moderation, the only significant relationships exist between OT and BDAC technology and OT and BDAC organizational learning. Surprisingly, the former reveals detrimental effects. This can be explained by the fact that, in general, SMEs avoid fruitless investments since their budgets do not allow them to invest in non-essential resources (Miller et al., 2021). This condition often locks SMEs into a state of frugality (Kuckertz et al., 2020). Decisions to invest more heavily in an area may stem from the belief that future revenues will compensate for this effort. Our results demonstrate that firms, despite their high levels of OT, may avoid unprofitable investments to adopt new technologies by favoring intuitive and heuristic decision-making (Elbanna et al., 2013). In addition, in the absence of an external trigger, firms may opt to restrict or streamline their technological architecture to avoid unnecessary internal complexity (Bayona et al., 2001). Under normal conditions, high OT could lead workmates to find solutions without the aid of

new technologies, or to collaborate with partners to support their activities (Teece, 1992).

Concerning the relationship between OT and technical skills, our findings highlight that managers do not need to hire or train skilled employees until an external factor intervenes. Our analysis reveals a similar outcome for the relationship between OT and managerial skills. Concerning the cultural dimension of BDAC, in the absence of EH, our results indicate that SMEs do not change their mindset, meaning that a higher OT could lead to preserving the current organizational culture identity.

The framework significantly changes when EH acts as a moderator. Indeed, our findings support all the hypotheses presenting EH as a moderator except for the OT-data relationship. This means that OT does not enable data improvement, so firms operating in a hostile environment should concentrate on acquiring the right data rather than more data (Bradlow et al., 2017; Janssen et al., 2017). An excessive amount of data could, in fact, undermine the decisional processes (Merendino et al., 2018). As these results demonstrate, when EH grows, firms with high OT may prefer to implement new technologies by leveraging more advanced technical skills rather than acquiring and integrating additional data from sources of questionable quality; this would avoid creating information overload.

Developing an adequate technological architecture is necessary to cope with hostile external environments, and OT serves as the foundation for deploying more advanced technologies successfully. OT and technologies together allow firms to define data-based strategies by connecting workmates along different hierarchies (Mikalef et al., 2019b). In these terms, technology serves as a tool for democratization.

As EH poses new challenges, it is increasingly urgent for organizations to have the ability to acquire, analyze, and exploit data with greater speed and precision. In this environment, firms need professionals who can gain strategic insights from data (De Mauro et al., 2018). When OT is higher,

superiors are more prone to democratize decision-making by entrusting subordinates who have the right skills with this responsibility (Anderson, 2015). Therefore, management is more likely to invest in training employees to perform tasks more effectively. In this regard, OT underpins the development of technical capabilities in hostile environments. Our results show that a similar trajectory characterizes the relationship between OT and managerial skills.

Considering the cultural dimension of BDAC, the findings indicate that in a hostile environment, firms need to transform their culture by fostering a data-driven mindset, encouraging transparent and open communication, and promoting continuous learning mechanisms (Bargoni et al., 2024). The transition toward a data-driven culture also implies prioritizing data-informed decisional processes, breaking down silos to facilitate information sharing across departments, and investing in training programs to enhance employees' analytical skills and technological proficiency (Anderson, 2015; Persaud and Zare, 2024). The effect of OT on a data-driven culture is related to the greater propensity of management to invest in employee training (Mikalef et al., 2019a), assuming the investment will bring positive returns. Vertical trust is basic for realizing this assumption (McCauley and Kuhnert, 1992) since managers are more prone to undertake strategic investments when they trust their subordinates' ability to perform tasks effectively and responsibly.

Cultivating a data-driven culture means the value of big-data information overrides human intuition (Gupta and George, 2016; McAfee and Brynjolfsson, 2012), implying that management tasks employees who possess the appropriate skills with extracting meaning from data. Therefore, such a cultural change is more likely when OT permeates the various functional areas and encompasses workmates along the top-down hierarchical scale (Anderson, 2015).

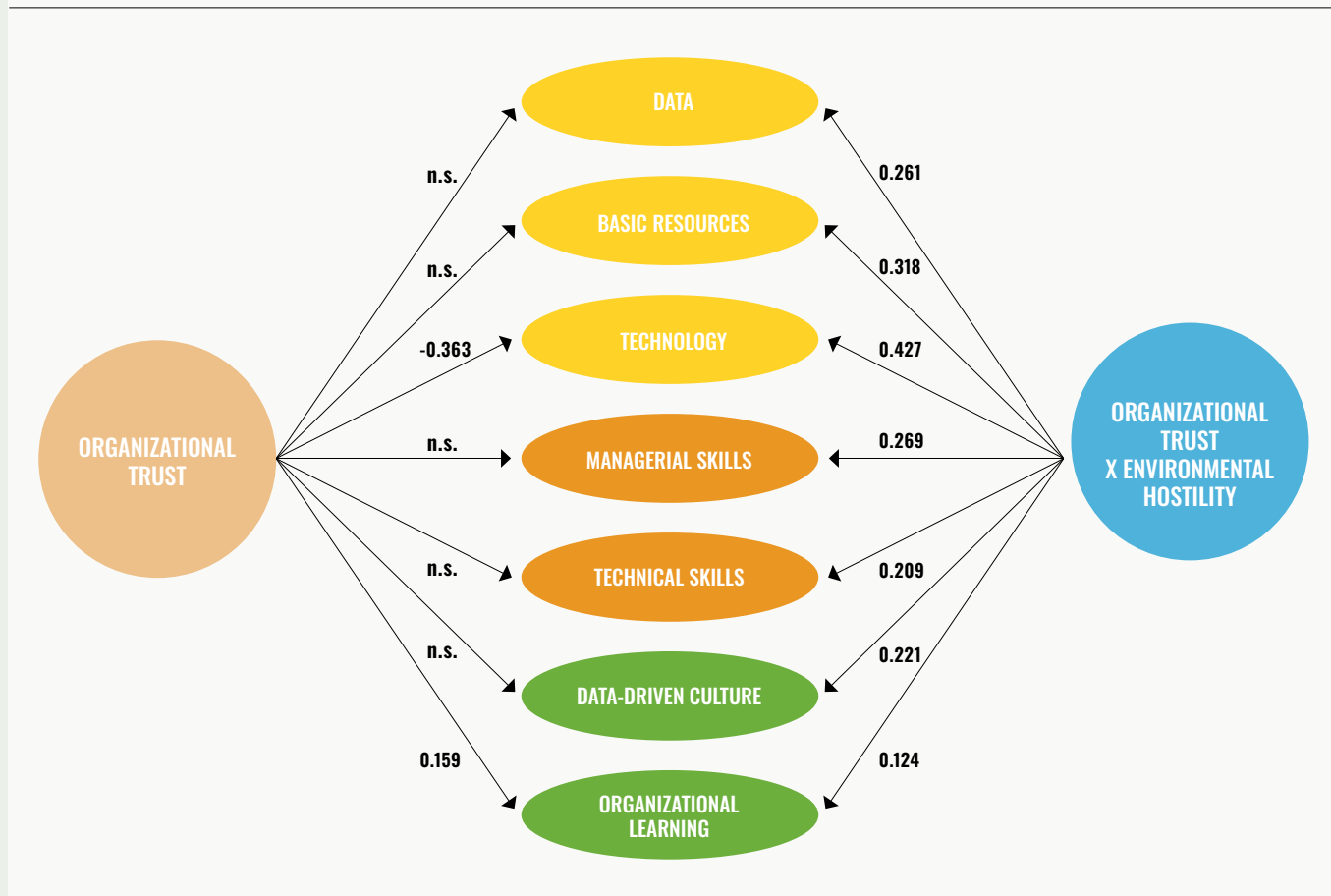
The external environment is crucial in driving BDAC development. Firms need OT to make their strategic processes more democratic along the

TABLE 1. RESULTS FROM PLS-PM

Hypothesis	Relationship	Estimate	t-value	Bootstrapping confidence interval	Hypothesis testing
H1a	OT $\Rightarrow$ data	-0.182	-2.519	(-0.327, 0.171)	Not supported
H1b	OT $\Rightarrow$ basic resources	-0.040	-0.556	(-0.195, 0.130)	Not supported
H1c	OT $\Rightarrow$ technology	-0.363 ***	-5.482	(-0.471, -0.239)	Not supported
H1d	OT $\Rightarrow$ managerial skills	-0.042	-0.574	(-0.172, 0.092)	Not supported
H1e	OT $\Rightarrow$ technical skills	0.091	1.253	(-0.062, 0.237)	Not supported
H1f	OT $\Rightarrow$ data-driven culture	-0.015	-0.210	(-0.148, 0.121)	Not supported
H1g	OT $\Rightarrow$ organizational learning	0.159	2.177	(0.011, 0.304)	Supported
H2a	OT x EH $\Rightarrow$ data	0.261 ***	3.614	(-0.198, 0.458)	Not supported
H2b	OT x EH $\Rightarrow$ basic resources	0.318 ***	4.460	(0.156, 0.485)	Supported
H2c	OT x EH $\Rightarrow$ technology	0.427 ***	6.442	(0.247, 0.582)	Supported
H2d	OT x EH $\Rightarrow$ managerial skills	0.269 ***	3.716	(0.173, 0.436)	Supported
H2e	OT x EH $\Rightarrow$ technical skills	0.209 **	2.884	(0.104, 0.382)	Supported
H2f	OT x EH $\Rightarrow$ data-driven culture	0.221 **	3.025	(0.095, 0.396)	Supported
H2g	OT x EH $\Rightarrow$ organizational learning	0.124	1.695	(0.003, 0.301)	Supported

*** p-value < 0.001; ** p-value < 0.005; * p-value < 0.01; Bootstrapping based on 5000 samples

FIGURE 2. ESTIMATED RELATIONSHIPS OF PLS-PM



entire decision-making chain (Anderson, 2015). Under constrained conditions, the ability to process information and make assessments may fail for decision-makers (Chen et al., 2015; Dubey et al., 2020). Instead, cultivating OT helps managers develop BDAC to avoid erratic decisions when facing hostile environments (Mitchell et al., 2011). In summary, as EH intensifies, firms need to adopt innovative tools that make decision-making more flexible and effective. Data is latent knowledge, while OT is a knowledge conduit, indicating a natural predisposition of the firm to foster internal flows of knowledge. By leveraging the right combination of OT and BDAC, firms can improve their capacity to transform information into structured knowledge (Nonaka, 1994). Moreover, as EH increases, OT becomes a catalyst for innovation and resilience. The success of this process is crucial to boost competitiveness in rapidly changing, knowledge-intensive environments.

Theoretical implications

Several theoretical implications arise from our study. Building on the previous literature, this paper aims to clarify whether OT is an antecedent of BDAC, and which of its dimensions OT nurtures. In addition, this study evaluates contextual conditions by analyzing the effect of the interplay between OT and EH on the development of BDAC. First, our work contributes to enriching trust and big data literature by exploring the relationship between OT and the multiple dimensions of BDAC. This contribution helps to deepen our knowledge of the antecedents of BDAC (Huynh et al., 2023) while providing insights into OT as a social foundation for dynamic capabilities (Fainshmidt and Frazier, 2017). Our results highlight the contingency-dependent nature of the relationship between OT and BDAC, unveiling the significant role of OT as a driver of BDAC when specific environmental conditions exist in the competitive scenario. These results only partially support previous literature theorizing the enabling role of OT and collaborative culture in successfully embracing the data-driven paradigm (Anderson, 2015; Kayabay et al., 2022). Unpacking

the multidimensional nature of BDAC, this study shows that OT directly contributes to improving organizational learning, while higher levels of OT discourage the development of the technology dimension. However, OT does not significantly affect the other BDAC dimensions.

Second, this study assesses the role of EH as a moderator, responding to a specific literature gap regarding the effects of environmental conditions in setting strategic boundary conditions shaping the development of BDAC (Huynh et al., 2023). While previous literature primarily focused on analyzing the interaction between environmental factors and BDAC in achieving specific outcomes (Mikalef et al., 2019; Mikalef et al., 2020; Wamba et al., 2020), this study concentrates on the interplay between environmental conditions and a potential antecedent of BDAC. By understanding the influence of these external factors, researchers can derive more precise and context-specific insights, ensuring that their findings are robust and applicable to real-world scenarios.

Third, this paper adds empirical evidence to the niche focusing on BDAC development in SMEs, which academic research has just begun to explore (Maroufkhani et al., 2023; Omrani et al., 2024). Our findings expand the current body of knowledge by showing that BDAC in SMEs is inherently trust-based and contingency-dependent.

Managerial implications

From a managerial point of view, our research highlights how essential it is for firms to regularly monitor their level of OT when transitioning to a data-driven organizational model. Firms can use different tools to assess OT. For example, anonymous surveys gauging employees' perceptions of trust within the organization can provide valuable insights. By offering feedback sessions where employees can discuss their concerns and share their experiences, organizations can identify trust-related issues. Another effective OT monitoring tool is a trust audit to evaluate the quality of communication and collaboration, and the transparency of practices. Executives should

also invest in social relationships and create a stronger sense of community (Gratton and Erickson, 2007) by promoting team-building activities, social events, and initiatives that encourage creative collaboration and learning (e.g., “serious games”).

This paper underscores the importance of the social fabric within the organization as the foundation for dynamic capabilities and competitive advantage, a force with the potential to shape collective learning and action. These findings suggest that to effectively develop BDAC, firms should prioritize initiatives aimed at building and nurturing trust among employees and managers, including transparency in communication, accountability at all levels of the organization, and fair treatment of employees. For example, adopting a rational vertical communication style and setting clear employee performance goals can enhance transparency and accountability. At the same time, engaging in CSR activities by implementing fair employment practices and reward systems contributes to higher job satisfaction and OT (Castaldo et al., 2023; Zhao et al., 2022).

As AI is becoming a core component of business activities and the development of BDAC, firms must ensure that their employees trust related technologies (Glikson and Woolley, 2020). Managers should foster trust in AI by ensuring transparency in how AI systems operate within the organization, making such systems explainable and comprehensible outside the “black box,” and establishing guidelines and ethical standards for fair AI use. Encouraging AI-human collaboration means designing user-friendly systems that are seamlessly integrated into existing workflows and providing ad hoc training sessions as well. Creating feedback mechanisms, AI communities, and timely sharing procedures can have the dual effect of shoring up trust in AI and reinforcing OT.

Also, firms should proactively adapt their strategies and practices to respond effectively to EH. This may involve conducting regular assessments of the competitive scenario, identifying potential threats and opportunities, and adjusting organizational processes and priorities accordingly.

In addition, by developing contingency plans with specific behavioral guidelines, firms can not only have rapid responses to environmental changes, but they can also help instill a sense of safety in employees and enhance mutual trust.

CONCLUSION, LIMITATIONS, AND FUTURE RESEARCH DIRECTIONS

The aim of our work is twofold: first, we examine whether OT serves as an antecedent to the individual dimensions of BDAC; second, we assess whether EH is a significant moderator in the relationship between OT and the dimensions of BDAC. Our results suggest that OT, under conditions of EH, plays a crucial role in enhancing BDAC, as it significantly influences various dimensions. Our results offer fresh insight into BDAC in SMEs and expand the current body of knowledge.

However, our work has some limitations that introduce new opportunities for research and managerial practice. As a first limitation, this study does not consider other variables that could affect the relationship between OT, BDAC dimensions, and EH. Therefore, future research should identify and analyze antecedents of BDAC and their relationships with OT. At the same time, it is noteworthy that OT could potentially play a dual role in this framework as both an antecedent of BDAC and an outcome. Future studies could enrich this feedback-loop perspective by conducting quantitative and qualitative analyses. In addition, EH is not the only exogenous variable that significantly influence the relationship between OT and BDAC. Environmental dynamism, turbulence, and uncertainty could represent other incidental external variables. Future research may concentrate on these variables to verify the generalizability of the results.

This study may also be affected by bias due to the single respondent. Moving forward, this limitation could be overcome by interviewing several informants for the same statistical unit. In addition, future research could consider samples with a higher concentration of younger managers to underscore

the potential generational implications of the study. For example, the literature highlights the fact that different generations (e.g., X and Y) can have different perceptions of the transition toward digital transformation and data-driven configurations of processes and workplaces, culminating in tensions, bottlenecks, and organizational breakdowns.

Therefore, qualitative research could uncover the trust-based mechanisms that can prevent such potential downsides, while quantitative research could analyze the inter-generational impact of OT on the dimensions involved in data-driven or digital transformations. Lastly, as this work may fail to capture generalizations beyond a single country or industry, future studies should focus on cross-country and cross-industry analyses to expand the boundaries of this research.

MANAGERIAL IMPACT FACTOR

- In hostile environments, OT facilitates the adoption of a data-driven culture, the development of technical and managerial skills, the empowerment of employees, and more effective data management.
- In the absence of a trigger from the external environment, OT is less effective in determining the development of BDAC.
- The interplay between OT and EH leads managers to adopt advanced technologies to implement data-driven decision-making, improving information processing and knowledge sharing.
- Managers should address EH by adjusting strategies to assess the competitive landscape, identify threats, and fine-tune organizational processes.
- Managers can promote surveys, creative activities, and CSR to monitor and foster OT, and encourage responsible AI development to strengthen a sense of community and build trust in technology.



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