Int. J. Production Economics 277 (2024) 109403

Contents lists available at ScienceDirect

International Journal of Production Economics

journal homepage: www.elsevier.com/locate/ijpe

A socio-cognitive theorisation of how data-driven digital transformation affects operational productivity?

Mohsin Malik [a,*], Amir Andargoli [a], Imran Ali [b], Roberto Chavez [a]

[a] School of Business, Law and Entrepreneurship, Swinburne University of Technology, Hawthorn, VIC, 3122, Australia
[b] School of Business and Law, Central Queensland University, Australia

ARTICLE INFO

Keywords:
Socio-cognitive theory
Cognitions
Psychological safety
Employee involvement
Process improvement
Data-driven digital transformation
Operational productivity

ABSTRACT

The literature on the antecedents of successful data-driven digital transformations needs clarity on if and how employees' cognitions and behaviours have any bearing on data-driven digital transformations with implications for operational productivity. This paper addresses this gap by drawing on socio-cognitive theory to examine how employees' cognitions (psychological safety) shape individual behaviours (employee-led process improvement) to affect organisational attainments such as data-driven digital transformations and operational productivity. A theoretical framework linking psychological safety to operational productivity through individual and serial mediations of 'employee-led process improvement' and 'data-driven digital transformation' is statistically tested by collecting survey data from 183 healthcare providers in Australia. The results indicate that when employees' perceptions of interpersonal risks are allayed (psychological safety), it has a significant positive effect on operational productivity directly and indirectly through the individual and serial mediations of employee-led process improvement and data-driven digital transformations. The socio-cognitive theorisation of psychological safety as the driving mechanism that facilitates employee-led process improvement, data-driven digital transformation and operational productivity is a first in the academic literature with implications for both theory and practice.

1. Introduction

Digital technologies are both a source of disruption and a trigger for the strategic organisational responses to exploit the opportunities afforded by digital technologies (Vial, 2019). Organisational strategic responses to harness the potential of digital technologies are operationalised through initiatives such as digital transformations (Hanelt et al., 2021). Digital transformations support firms in governing and implementing digital technologies to transform the customer value (new product development) and the value creation processes (process innovations) (Vial, 2019). Thus, digital transformations are critical to contemporary operations and supply chain management because they enable businesses to remain competitive in this digital age (Battistoni et al., 2023). Despite the potential to transform operations and supply chains, the evidence from practice on digital transformations is not encouraging. For example, a Boston Consulting Group study indicated that 65% of the 850 surveyed firms did not achieve the intended digital transformation results (Forth et al., 2021). Specifically, the success of digital transformations for some industries such as healthcare providers – the research context for this study – are particularly low at only 16% (Forth et al., 2022). This suggests that the healthcare context has unique characteristics such as high risks and patient safety, complex regulatory environment, ethical considerations such as data privacy and evolving standards and practices that make healthcare digital transformation particularly challenging (Malik et al., 2024). The academic literature also provides equivocal results on digital transformations, in general, citing a lack of clarity on the antecedents and the intermediate steps that are required to digitally transform operations (Nasiri et al., 2022). To address this, the literature has mostly theorised a) the organisational antecedents and mechanisms that foster dynamic capabilities necessary for digital transformations and b) how firms acquire external complementary resources and capabilities for digital transformations (Malik et al., 2024). In these theoretical explanations, however, the social agency is assumed to rest with management for digital transformation (Malik et al., 2024). Often overlooked are the factors related to employees that influence digital transformations. We address this literature void by drawing on the socio-cognitive theory to examine how employees' cognitions (psychological safety) shape their individual

* Corresponding author.
E-mail addresses: mmalik@swin.edu.au (M. Malik), aandargoli@swin.edu.au (A. Andargoli), i.ali@cqu.edu.au (I. Ali), rchavez@swin.edu.au (R. Chavez).

https://doi.org/10.1016/j.ijpe.2024.109403
Received 28 October 2023; Received in revised form 22 May 2024; Accepted 5 September 2024
Available online 6 September 2024

behaviours (employee-led process improvement) with implications for organisational attainments such as data-driven digital transformations and operational productivity.

The literature in operations and supply chains management is now drawing a distinction between 'digital transformation' and 'data-driven digital transformation' (Papanagnou et al., 2022). This differentiation arises from the recognition of a 'mutually constitutive relationship' between big data and digital transformation. Big data and predictive analytics are important elements of a digital transformation because they generate actionable insights for managerial decision-making (Mikalef et al., 2019). The generation of big data, however, is a pre-requisite of predictive analytics and algorithmic decision-making (AlNuaimi et al., 2021; Hussain et al., 2023). This is enabled through the digitalisation of organisational processes and the adoption of digital technologies (digital infrastructure), data portability and inter-connectivity (Günther et al., 2017). This mutually constitutive relationship between big-data and digital transformation is more implied than direct in the extant literature. For example, the focus of Vial (2019)'s conceptualisation of a digital transformation was on the adoption of digital technologies such as social media, mobile and cloud technologies, analytics, and the internet of things for organisational improvements. The principal mechanism, however, through which the digital technologies enable organisational improvements is by generating big data and conducting analytical procedures performed on the big data to derive useful insights (Günther et al., 2017; Hussain et al., 2023). Thus, predictive analytics and data driven decision making are the core of a digital transformation conceptualisation. Papanagnou et al. (2022) address this by introducing a specific data focus in Vial (2019)'s conceptualisation of digital transformation and refer to it as a data driven digital transformation'. They define a data-driven digital transformation as *'a process that aims to improve a firm by triggering significant changes to its capabilities and design through the use of various technologies and data'* (Ibid:3). Data-driven digital transformation puts the spotlight on how information and data enable firms to profoundly alter decision-making processes and structures within and between organisations by incorporating digital technologies (Li, 2020). The use of predictive analytics and data-driven decisions to alter intra and inter organisational processes is now fast emerging as the contemporary way of managing operations and supply chains in this digital age (Dubey et al., 2022). Thus, a data-driven digital transformation enables strategic deployment of digital technologies and data-sharing practices with implications for operational performance (Papanagnou et al., 2022). This makes operational productivity as the overarching objective of a data-driven digital transformation; therefore, operational productivity has been cast as the outcome of interest for this research. The literature, however, is still exploring the antecedents of successful data-driven digital transformation (Nasiri et al., 2022). Particularly, there is not enough clarity on if and how employees' cognitions and behaviours have any bearing on data-driven digital transformations and consequently, operational productivity. The socio-cognitive theorisation employed in this research addresses this literature gap, Socio-cognitive theory explains human functioning through triadic interactions between social environment, human cognitions, and behaviours (Bandura, 2001). Framing the socio-cognitive theorisation of human functioning for organisational attainments (Wood and Bandura, 1989), we conceptualise employees' psychological safety as the cognition that affects both employees' behaviours and organisational outcomes. The employees' behaviour relevant to an operations context is employee-led process improvement (Narayanan et al., 2022). In our research, we also propose that employee-led process improvements are facilitated by creating an environment of psychological safety within the organisation. The organisational outcome of interest in this research is operational productivity, which in this digital age, also requires data-driven digital transformation as an intermediate organisational attainment. Informed by these theoretical arguments, we propose the following research question:

"How do employees' cognitions and behaviours influence data-driven digital transformation and operational productivity?"

By answering this research question, we provide new and original insights on how the socio-cognitive mechanisms such as psychological safety influence operational productivity through the individual mediations of a) employee-led process improvements and b) data-driven digital transformation and a serial mediation comprising of both employee-led process improvements and data-driven digital transformation. The empirical validation of psychological safety, as the driving mechanism that facilitates employees-led process improvement' and data-driven digital transformation to affect operational productivity, is a new finding in the extant literature with implications for both theory and practice. To make these important contributions, Section 2 provides further details of the socio-cognitive theorisation employed in this research. The theoretical constructs underpinning the proposed conceptual model are also introduced and defined in Section 2. Section 3 develops hypotheses and Section 4 describes the employed methods and statistical results. The theoretical and practice implications of the statistical results obtained in this research are presented in section 5. This research is concluded in Section 6.

2. Theoretical framework

2.1. Socio cognitive theory

Socio-cognitive theory explains human functioning in terms of a triadic relationship between social environment, human cognitions (personal processes) and behaviours (outcomes) – both at the individual level and at the organisational level (Bandura, 2001; Wood and Bandura, 1989). Socio-cognitive theory was developed to explain individual and organisational learning by positing that people can acquire new behaviours and knowledge by observing their social environments (Bandura, 2001; Schunk and DiBenedetto, 2020). This suggests that the individual behaviour is a function of human cognitive processes i.e., individuals' perception or state of mind mediates the relationship between a social environment and the observed behaviours (outcomes) (Bandura, 1988, 2001). Self-efficacy or the belief in one's ability to perform specific tasks was the initial cognition, identified by socio-cognitive theory, as being instrumental in shaping people's behaviours and performance (Wood and Bandura, 1989). Since then, other cognitions such as social comparisons, values (perceived useful of learning), outcome expectations and attributions (perceived causes of outcomes) have been linked to efficacious individual learning behaviours (Schunk and DiBenedetto, 2020).

The triadic interactions of social environment, cognitions and behaviours also function as an important constituent of organisational learning and performance (Wood and Bandura, 1989). The focus of the socio-cognitive theorisation of organisation has been on the cognitions that underpin managerial decision-making, and the implications of managerial choices constitute the behaviour or performance at the organisational level (Bandura, 1988). The literature examining the cognitive processes undergirding managerial decision-making reveals two distinct conceptions of managerial capabilities with contrasting organisational performances (Wood and Bandura, 1989). An induced conception of capability as an 'acquirable skill' through experimentation enable managers to achieve higher organisational attainments (Ibid: 373). On the contrary, the organisational attainments deteriorated when decision-making was construed as reflective of the inherent cognitive abilities of managers (Ibid: 374). The induced and reflective conceptions of capabilities and their contrasting performances are similar to psychological safety – an interpersonal construct (Edmondson, 1999) that emerged a little later than the socio-cognitive theory but has gained a strong traction in the management and organisation literature. Like the induced conception of capability, psychological safety enables individuals, teams and organisations to learn, and perform (Edmondson and Lei, 2014). Organisational performance is a function of how individuals collaborate, learn and work together as highly interdependent work teams and interpersonal risks in experimental learning need to be allayed with a psychologically safe work environment (Newman et al., 2017). Thus, psychological safety constitutes an employee cognition that is afforded to individuals by a work or organisational culture (social environment), which reduces the interpersonal risk associated with work mistakes, therefore, enabling higher personal, team and organisational attainments (Edmondson and Lei, 2014). Framing these relationships along social cognitive theory's triadic interactions between human cognitions, environment, and outcomes, we conceptualise employees' psychological safety as the cognition that affects both employees' behavioural outcomes and organisational outcomes. The employees' behavioural outcome relevant to our research is the 'employee-led process improvements', which is facilitated by an environment of psychological safety (cognition) afforded to the employees by a social environment (organisation). The organisational outcome is the operational productivity, which in digital context, requires intermediate step such as data digital transformation. The socio-cognitive theory origin lies in the field of educational psychology where it has been frequently used to explain human learning across diverse contextual settings. Now, this theoretical framework is increasingly gaining traction in the domain of operations and supply chain management. For example, Yang et al. (2017) explained operational efficiency and employees' self-efficacy through socio-cognitive theory. Similarly, Wu et al. (2021), Le (2023), and Wei et al. (2023) also used a socio-cognitive lens to theorise operations and supply chain phenomena. Furthermore, these studies employed a positivist research design, which is also similar to the theorisation employed in the current research and depicted in Fig. 1. Next, we formally define the theoretical constructs comprising Fig. 1.

2.2. Psychological safety

Respect and trust for one another and continuous and open communication are key elements for employees to work together, share responsibilities, make commitments and decisions, and finally finish with their assigned tasks (Nembhard and Edmondson, 2006). Psychological safety emerges as a key element that encourages mutual respect and trust and the willingness to share ideas and knowledge without the risk of being judged (Choo et al., 2007; Edmondson, 1999; Lee et al., 2023). Psychological safety creates a feeling of security and trust among employees to share their views, value others' ideas and work toward the achievement of work goals (Baer and Frese, 2003; Newman et al., 2017). It is in an organisation's best interest to create a work environment that promotes psychological safety to help employees overcome fears, anxiety, and defensiveness, and feel comfortable at the time of sharing their ideas and contributions; all main aspects that enable collaboration and continuous improvement (Nembhard and Edmondson, 2006). In this study, we define psychological safety as a 'shared belief held by employees that their work environment values their contributions and talent, and is safe to ask questions, ask for help, share views, knowledge and concerns, and admit making mistakes without the risk of being penalised' (Edmondson, 1999; Lee et al., 2023; Lee et al., 2011).

2.3. Employee-led process improvement

Process improvement initiatives have been regarded as a socio-technical system of integrated practices that target organisational improvements by reducing process variability and non-value adding activities (Shah and Ward, 2003, 2007). While the 'technical' element includes operating practices and techniques that promote process efficiency, the 'social' component refers to human and cultural traits (Cullinane et al., 2014). The social dimension is central to effective process improvements because of its focus on employee involvement through empowerment, teamwork, responsibility and opportunity, thus, fostering motivation in employees (Huo and Boxall, 2018). Without people involvement, technical tools and techniques are unlikely to show its full benefits (AlNuaimi et al., 2021; Cullinane et al., 2014). Job involvement is at the heart of employee-led process improvement because it engenders employee support through resource-provision, task-allocation, technical advice, and listening to opinions and concerns (Huo and Boxall, 2018). Employee-led process improvement is adapted in this study to a hospital setting to identify a conducive set of social practices that could be implemented in hospitals. Specifically, we build on the work of Narayanan et al. (2022) to define employee-led process improvement as a 'set of social practices that encourage teamwork, empowerment and process/quality improvement in a hospital environment'.

2.4. Data-driven digital transformation

Data driven digital transformation of an organisation involves the use of digital technologies and the data these digital technologies produce to introduce significant improvements and changes to operations, strategies, and customer experiences (Papanagnou et al., 2022). The digital infrastructure developed in a digital transformation produces information and data allowing managers to revisit intra and inter-organisational relationships and processes for more informed operations decision-making (Dubey et al., 2022; Khan et al., 2023). Emerging digital technologies such as artificial intelligence, internet of things, and predictive or big tata analytics generates insights that aid managerial decision-making to redesign organisational processes for effectiveness and efficiency purposes (Li, 2020). Thus, data-driven digital transformations are complementary to or build on the core operations tenets of process improvement and reengineering (Holmström et al., 2019). Despite this promise to improve operational performance, the evidence from practice suggests that many digital transformations fail to deliver the desired results (Forth et al., 2021). One explanation for these below expectations performance is that data-driven digital transformation is a socio-technical artefact comprising of technology and the technical tasks to generate big data (Gupta et al., 2020) and the organisational factors and peoples' skills and knowledge (Mikalef et al., 2019). The lack of appropriate infrastructure and a variation in employees' skills for big data analytics is particularly relevant to a healthcare sector (Hussain et al., 2023). Thus, data driven digital transformation is dependent upon the individuals' and organisation's knowledge of digital technologies and their ability to generate actionable insights from the data generated by the digital technologies (Mikalef and Krogstie, 2020). This socio-technical artefact view of data-driven data digital transformation enabled a socio-cognitive theorisation employed in this research.

2.5. Operational productivity

The concept of operational productivity refers to the ratio of the total output in relation to the total input in any transformation process (Ong et al., 2021). Specifically, operational productivity indicates how transforming resources such as raw materials, people and information have been utilised and transformed in relation to the resulting products produced or services delivered (Möldner et al., 2020). Thus, the lesser the resources utilised in a transformation process, the higher the productivity (Alkhaldi and Abdallah, 2019). Efficient resource utilisation is one of the core principles of operations and supply chain that has been shown to generate competitive advantage (Al-Qubaisi and Ajmal, 2018). Process improvements have been directly linked to operational productivity because of the minimisation of errors and non-value adding activities in the input-output transformation process, therefore, enabling efficient use of resources (Ong et al., 2021). The advent of digital technologies is now also being viewed as an opportunity to fundamentally revisit and improve value creation processes with implications for operational productivity (Holmström et al., 2019). Cost, quality, and delivery are operational capabilities directly associated with productivity as less resources, free-from-error products/services and fast and dependable processes all contribute to productivity (Shah and Ward, 2007). Operational productivity has been adapted in this study to reflect ‘operational capabilities that target the efficient use of resources and the input-output ratio in a hospital setting’.

3. Hypotheses development

3.1. The mediation effect of employee-led-process improvement

The extant literature suggests that there are positive effects of employees’ perceptions of psychological safety on individual, team, and organisational performances. Specifically, for organisational performance, there is empirical evidence linking psychological safety directly with financial performance (Baer and Frese, 2003), manufacturing process innovation (Lee et al., 2011), and operational performance (Lee et al., 2023). Similarly, for team performance, the literature links psychological safety directly with creative thinking and risk taking (Edmondson and Lei, 2014), individual creative self-efficacy and team operational efficiency (Yang et al., 2017). These interpersonal attributes in turn affect innovation performance at the organisational level (Edmondson and Lei, 2014) which implies that psychological safety has both direct and indirect effects on performance. The indirect effects of psychological safety on performance are theorised and empirically tested in the literature from a theoretical standpoint. For example, social exchange theory has been employed to suggest that social interactions between employees and the organisation mediate the relationship between psychological safety and performance (Newman et al., 2017). We, however, draw on the socio-cognitive theory’s triadic interaction to suggest human behaviour (employee-led process improvement) as the first intervening step between psychological safety and operational productivity.

Human behaviour is central to effective process improvements because the employees are more likely to spend discretionary effort if they feel empowered and engaged with process improvement efforts (Huo and Boxall, 2018). A psychological safe work environment is likely to motivate employee engagement because it enables divergent thinking, creativity, and risk-taking (Edmondson and Lei, 2014). The feeling of security and trust among employees in a psychologically safe work environment allows experimentation and open sharing of conflicting views by employees because they feel that errors and conflicting viewpoints will not be held against them (Newman et al., 2017). Thus, a feeling of psychological safety by employees is likely to facilitate employee-led process improvement with implications for operational productivity such as reduced errors, lowered overhead cost and faster service. This suggested mediation of employee-led process improvement builds on similar argumentation in the literature that process innovation may mediate the relationship between psychological safety and firm performance (Edmondson and Lei, 2014). The socio-cognitive theorisation, however, provides more nuance and specificity to this suggested relationship by focussing on human behaviour (employee-led process improvement) as the intervening step between employees’ cognition of psychological safety and the organisational outcome of operational productivity. Specifically, we suggest.

H1. *Employees led process improvement mediates the relationship between psychological safety and operational productivity.*

3.2. The mediation effect of data-driven digital transformation

The socio-cognitive theorisation employed in this research suggests data-driven digital transformation as one the two organisational attainments considered in this research. The triadic interactions of socio-cognitive theory suggests both direct and indirect relationship of data-driven digital transformation with employees’ cognition of psychological safety. In this subsection, we propose a direct relationship between psychological safety and data-driven digital transformation with implications for operational productivity. That is, psychological safety is a key driver in creating a workplace culture conducive to innovation and change. This culture, in turn, facilitates the organisation to embrace data-driven digital transformation, thereby, enhancing efficiency, process optimisation, and supporting more informed decision-making for increased productivity. Data-driven digital transformation improves operational productivity through a) strategic deployment of digital technologies and data-sharing practices to re-configure organisational resources (Hussain et al., 2023; Papanagnou et al., 2022), and b) by providing structures and resources to generate big data through the transfer and remote access of the digitised data and the interconnectivity (data portability) (Günther et al., 2017). Big data then can be utilised to perform several tasks that further guides a digital transformation. For example, big data is a great resource for organisations to sense and respond to environmental cues by transforming the current organisational resource base (Gupta et al., 2020). Furthermore, predictive analytics of big data leads to data-driven decision-making regarding the redesign of operations and supply chain processes to continuously improve operational performance (Papanagnou et al., 2022). These arguments delineate specific mechanisms through which data-driven digital transformation is likely to influence operational productivity.

Regarding the antecedents of data-driven digital transformation, the socio-cognitive underpinning employed in this research suggests employees’ cognition (psychological safety) as a potential facilitator. Data-driven digital transformation has been conceptualised as a socio-technical artefact comprising of digital technology to generate big data (Gupta et al., 2020) and the organisational factors and peoples’ skills and knowledge for generating useful insights from big data (Mikalef et al., 2019). Thus, data-driven digital transformation requires integration of digital infrastructure, the socio-technical expertise of employees and organisational learning (Mikalef et al., 2019). Employees socio-technical expertise for data-driven digital transformation requires development of new business, technical, managerial and leaderships skills and knowledge through experimentation (Hanelt et al., 2021). The trial-and-error approach to generate new bundles of socio-technical skills required for data driven-digital transformation (Vial, 2019) is more likely to be successful in a psychologically safe work environment where mistakes provide valuable organisational learning (Edmondson and Lei, 2014). Thus, psychological safety is likely to have a direct effect on data-driven digital transformation, and given the potential effects of data-driven digital transformation on operational productivity argued earlier, we suggest.

H2. Data driven digital transformation mediates the relationship between psychological safety and operational productivity.

3.3. Serial mediation of employee-led-process improvement and data-driven digital transformation

The two previous subsections develop arguments for individual mediation effects of employee-led process improvement (H1) and data-driven digital transformation (H2) for the relationship between psychological safety and operational productivity. These hypotheses entailed development of arguments linking psychological safety to a) employee-led process improvement (H1) and operational productivity and b) data-driven digital transformation and operational productivity (H2). There is a case, both from theoretical standpoint and from the emerging discourse on the digital transformation of operations and supply chains, to suggest a serial mediation of employee-led process improvement and data-driven digital transformation for the relationship between psychological safety and operational productivity (see H3 in Fig. 1). This requires additional argumentation establishing a link between employee-led process improvement and data-driven digital transformation. We do this now by suggesting an indirect relationship between psychological safety and data-driven digital transformation

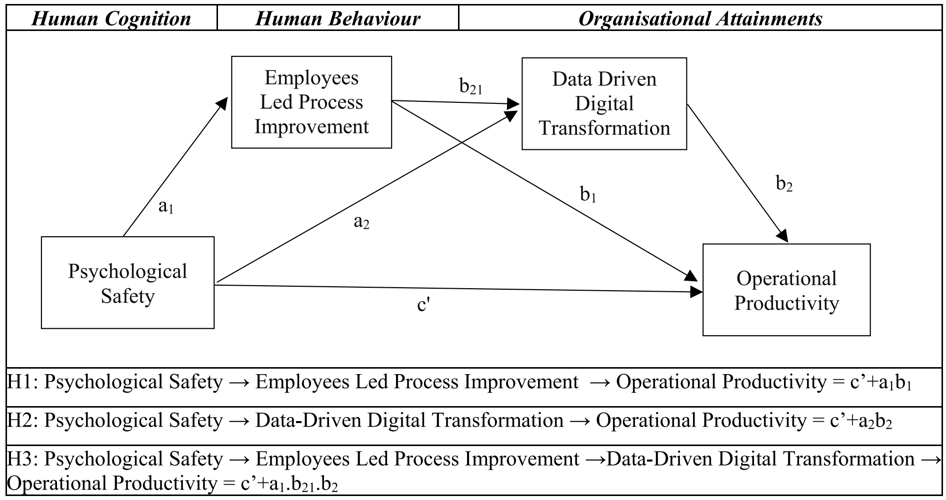

Fig. 1. A socio-cognitive theorisation of how data-driven digital transformation affects operational productivity.

through employee-led process improvement. The triadic interactions of socio-cognitive theory posit that human cognition (psychological safety) leads to human behaviours (employee-led process improvement) affecting organisational attainments (data-driven digital transformation) because organisations essentially represent group of individuals (Wood and Bandura, 1989). Thus, the employees' mutual cognitions are an important factor in shaping individual and organisational behaviours (Bandura, 2001). Furthermore, the emerging literature on the digital transformation of operations and supply chain is suggesting that the insights digital data generates enable managers to redesign organisational processes for effectiveness and efficiency gains (Li, 2020). This suggests that both process improvements and data-driven digital transformations are complementary to each other because they aim to revisit and improve value creation processes for operational productivity (Holmström et al., 2019). Both process improvements and data-driven digital transformation have also been conceptualised as "socio-technical artefacts", which puts the spotlight on employee engagement and empowerment (see Narayanan et al. (2022) and Gupta et al. (2020)). This implies that employee-led initiatives such as process improvement are also likely to affect data-driven digital transformation. Thus, taken together, the socio-cognitive theoretical framing and the recent assertions in the operations and supply chain literature, we suggest the following serial mediation effect.

H3. Employee-led process improvement and data-driven digital transformation serially mediate the relationship between psychological safety and operational productivity.

4. Methods and results

4.1. Research design, operationalisation, and data collection

This study follows a positivist research design in which we test *a priori* relationships depicted in Fig. 1. To test the proposed relationship, we developed a survey questionnaire and, at that stage, we had a decision to make: whether to a) develop new scales to measure theoretical constructs or b) leverage the existing scales available in the extant literature. Best practices in the methodological domain such as Hair et al. (2018, p. 663) suggests that *"When a previously applied scale is not available, the researcher may have to develop a new scale. The process of designing a new construct measure involves a number of steps through which the researcher translates the theoretical definition of the construct into a set of specific measured variables"*. This recommendation suggests a preference for established scales on two counts. First, the notion of validated (previously applied) scales implies that the scales have been empirically tested to exhibit reasonable psychometric properties such as content validity, unidimensionality, reliability and statistical validity (Hair et al., 2018). Thus, an established scale with proven psychometric properties gives researcher(s) confidence that they are effectively measuring the theoretical constructs of interest. Second, whenever available, validated scales save time because a rigorous new scale development and testing is time consuming (Hair et al., 2018). Therefore, we conducted a review of the existing literature to identify measurement scales that effectively capture the theoretical constructs relevant to our research. We successfully identified validated measurement scales that accurately represent the theoretical constructs of interest. As a result, we are confident in the validity of our findings due to the established psychometric properties of these scales. For example, the scale for psychological safety was borrowed from Edmondson (1999) and Narayanan et al. (2022). Employees led process improvement was also adapted from the validated scale used by Narayanan et al. (2022). Data driven digital transformation was borrowed from AlNuaimi et al. (2022) whereas operational productivity was measured using the validated scale used by Ong et al. (2021) and Alkhaldi and Abdallah (2019). Healthcare industry was chosen as the contextual setting to test the hypothesised relationship because of the significant challenges associated with its digital transformation (see Forth et al. (2022)). The scales for psychological safety and employees led process improvement were already adapted to a healthcare setting by the source studies. We adapted the scales for data driven digital transformation and operational productivity to a healthcare setting with the help of an expert panel comprising of industry experts and academics to establish content validity. To source potential informants for this research, we selected Australia because digital health transformation is at an advance stage in Australia, therefore, individuals making governing decisions in the Australian healthcare sector were deemed to possess the managerial insights to inform this research. We partnered with a market research firm with access to healthcare decision-makers to share the link of our survey with the potential respondents in an email. A total of 183 responses were obtained which became our final sample for this study. The demographic details of the respondents are provided in Table 1.

Our sample size of 183 observations meets the following two minimum sample size requirements for a measurement model and confirmatory factor analysis. First, Hair et al. (2018), p. 633 suggests a minimum sample size of 100-150 responses for models containing five or fewer constructs, each with at least three items (observed variables) and with high item communalities > 0.6. The CFA model results reported in Table 2 shows that our model meets the requirements of communalities of ≥ 0.6 and four theoretical constructs with at least three items. Second, we calculated the minimum sample size of 94

Table 1
Sample information.

Respondents' Experience (x = number of years)		
$x < 5$	116	63%
$5 \leq x \leq 10$	29	16%
$x > 10$	38	21%
Hospital Size (x = number of beds)		
$x < 101$	68	37%
$101 \leq x \leq 250$	43	23%
$x > 250$	72	39%
Hospital Speciality		
Women's hospitals	10	5%
Children's hospitals	10	5%
Cardiac hospitals	1	1%
Oncology hospitals	2	1%
Psychiatric hospitals	5	3%
General	140	77%
Other healthcare providers	15	8%

responses by using the Soper calculator (Soper, 2016). This calculator utilises the statistical work of Westland (2010) and the input parameters used to calculate the minimum sample size are a) four latent constructs, b) 19 observed variables/items, c) desired statistical power = 0.8, b) probability of type-1 error = 0.05, medium anticipated size = 0.35. Both Hair et al. (2018, p. 633) and Soper calculator (Soper, 2016) confirm that a sample size of 183 responses for this research is adequate to draw statistical inference.

Common method bias usually associated with self-reported survey responses was actively minimised through both ex-ante and ex-post measures. As an ex-ante measure, we ensured the complete anonymity of responses both in the invitation email to participate in the survey and at the first page of the survey. The literature suggests that an anonymous survey and the assurance to this effect minimises social desirability and acquiescence biases (Hulland et al., 2018). Another ex-ante measure we employed was that we did not label any theoretical construct nor provided any pointers through which the respondents could have guessed the theoretical relationships being examined. This measure is also likely to minimise common method bias (Hulland et al., 2018). The ex-post measures comprised of two statistical tests for the presence of common method bias. We initially tested for common method bias by performing a single factor confirmatory factor analyses (CFA) by constraining all indicator variables to one factor only. The model fit results of the single factor CFA model were CMIN/DF = 4.85, Tucker–Lewis Fit Index (TLI) = 0.71, Comparative Fit Index (CFI) = 0.72 and Root Mean Square Error of Approximation (RMSEA) = 0.15. This poor model fit showed that a single factor does not account for the major variance indicating that common method bias was not a major issue

Table 2
Confirmatory factor Analyses.

	Construct Indicators	Standard Coeff.	t-Values
Psychological Safety			
1	Employees of our hospital are able to bring up problems and tough issues.	0.82	11.55
2	Employees of our hospital feel comfortable checking with each other if they have questions about the right way to do something	0.71	9.84
3	It is difficult to ask other employees within the hospital for help.		
4	Employees' unique skills and talents are valued and utilised in this hospital		
5	If employees of our hospital make a mistake, it is often held against them	0.82	_a
Employees Led Process Improvement			
1	Our hospital's employees are allotted time during normal work hours to perform process/quality improvement	0.76	12.38
2	Cross-functional teams are used for process/quality improvement initiatives	0.87	13.96
3	Hospital employees are members of process/quality improvement teams.	0.90	14.67
4	Our hospital's employees are empowered to perform process/quality improvement	0.85	_a
Data Driven Digital Transformation			
Please indicate the level of your hospital's capabilities in following areas:			
1	In our hospital, we aim to digitalize everything that can be digitalized	0.71	_a
2	In our hospital, we collect large amounts of data from different sources	0.68	8.73
3	In our hospital, we aim to create more robust networking with digital technologies between the different business	0.87	11.01
4	In our hospital, we aim to enhance an efficient patient interface with digitality	0.79	10.14
5	In our hospital, we aim at achieving information exchange with digitality.	0.81	10.35
Operational Productivity			
Please rate the extent to which digital technology has improved each of the following:			
1	Number of errors (e.g., machine breakdown, service errors, and rework) in hospital have decreased	0.72	_a
2	All types of waste in resources and materials throughout hospital have minimized.	0.67	9.79
3	Hospital overhead cost has reduced.	0.74	9.65
4	The processing time to deliver healthcare services has reduced	0.87	11.38
5	The inputs (e.g., materials, capital, labour and energy) to deliver healthcare services has reduced	0.83	10.92
6	We have setup processes to make our healthcare services more efficient.	0.69	9.01
7	Overall healthcare productivity (more output is being produced for each unit of input) is outstanding	0.82	10.80

n=183 Model fit indices: CMIN/DF =2.03, IFI=0.94, TLI=0.93, CFI=0.94, RMSEA=0.07

All t-values ate significant to p < 0.005, _a indicates a parameter that was fixed at 1.0

indicator variables deleted because of low loadings and removed from further analyses

(Chavez et al., 2022; Hulland et al., 2018). After this initial confirmation, we performed a common latent factor test by comparing the measurement models fit indices with and without a common latent factor. The marginal difference (ΔTLI and ΔCFI <0.02) imply that the common method bias was not a major concern (Chavez et al., 2022; Hulland et al., 2018).

For sample nonresponse test, the literature suggests that non-respondents are more similar to late respondents and no statistically significant differences between early and late respondents imply that non-response bias is not a concern (Chavez et al., 2022). Therefore, we conducted a Mann-Whitney U two sample independent test to detect statistically significant differences between early respondents ($n_1 = 92$) and late respondents ($n_2 = 91$). All four theoretical constructs did not reveal any statistically significant differences across n_1 and n_2 which gave us confidence that non-response bias was not a concern.

4.2. Measurement model and data validity and reliability tests

Exploratory factor analysis (EFA) explores the data purely on statistical correlations without any theoretical considerations whereas a CFA is theory driven because the research objective is to test *a priori* measurement model derived from theory (Hair et al., 2018). Specifically, a CFA '*confirms the extent to which a researcher's a priory, theoretical pattern of factor loadings on prespecified constructs represent the actual data'* (Hair et al., 2018, p. 661) Given this, we did not employ EFA as it was not required given the research focus and objective. The CFA was performed in AMOS version 29 indicating absolute indices (CMIN/DF = 2.03 & RMSEA = 0.07) and incremental fit indices (IFI = 0.94 & CFI = 0.94) which met Hair et al. (2018)'s recommended acceptable thresholds of CMIN/DF ≤ 3, TLI & CFI ≥0.9 and RMSEA ≤0.08 (Tabe 2). The literature suggests that constructs indicators (variables/items) with factor loading < 0.50 show a limited contribution to the observed variance in measuring a theoretical construct (Hair et al., 2018). Therefore, in line with best practices such as Jafari et al. (2022), we removed two indicator variables/items from psychological safety due to factor loading < 0.5. We, however, fulfill the minimum requirements for measurement validity such as three survey questions with strong loadings for each theoretical construct (Hair et al., 2018).

The results of construct reliability and validity tests are reported in Table 3 showing satisfactory composite reliability scores of >0.7 and acceptable convergent validity because the average variance extracted (AVE) scores were more than 0.5 (Chavez et al., 2022; Hair et al., 2018). Discriminate validity was also established because the square roots of AVE scores were greater than the inter-construct correlations (Chavez et al., 2022; Hair et al., 2018).

4.3. Mediation analyses

The mediation hypotheses depicted in Fig. 1 are represented by the following three equations:

$$M_1 = i_{M1} + a_1 X + e_{M1} \tag{1}$$

$$M_2 = i_{M2} + a_2 X + d_{21} M_1 + e_{M2} \tag{2}$$

Table 3
Data reliability and validity test results.

Construct	CR	AVE	PS	PI	DT	OP
Psychological Safety (PS)	0.83	0.62	**0.79**			
Employee-Led Process Improvement (PI)	0.91	0.72	0.65	**0.85**		
Data Driven Digital Transformation (DT)	0.88	0.60	0.71	0.61	**0.77**	
Operational Productivity (OP)	0.91	0.59	0.64	0.59	0.66	**0.77**

CR = Composite Reliability, the bold fonts in diagonal show square root of Average Variance Extracted (AVE).

$$Y = i_Y + c' X + b_1 M_1 + b_2 M_2 + e_Y \tag{3}$$

Where $X =$ *Psycological safety*, $M_1 =$ *Employee Led employee improvement*, $M_2 =$ Data Driven *Digital* Transformation, $Y =$ *Operational Productivity*, $i =$ *constant*, $e =$ *error and* $a_n\ b_n d_{mn}$ *are path coefficients from Figure* 1.

The two mediators in Fig. 1 and equations (1-3) represent 3 specific indirect effects which were hypothesised to affect operational productivity (H1-H3). Testing for complex individual and serial mediation hypotheses depicted in Fig. 1 requires a) statistical modelling of specific indirect effects and b) a bootstrapping method to test significance of the indirect effects. Hayes Process Macro for SPSS (Hayes, 2017) is an advance statistical software which fulfils both these modelling requirements to operationalise a complex mediation analysis to test multiple specific indirect effects (Malik et al., 2024). Therefore, we used Model 6 of Process macro (Hayes, 2017) which represents Fig. 1 to perform two individual and one serial mediation analyses. To control this statistical analyses, prior findings in the literature suggest that larger firms are typically resource munificent which is likely to have an impact on digital transformations (Lin et al., 2022). Therefore, as suggested by Paré et al. (2020), hospital size measured in terms of number of hospital beds was used as a control variable for this analysis.

A summary of the direct effects (Table 4) and mediation analyses (10,000 bootstrap samples) with the hypothesis tests results is reported in Table 5. The empirical findings in Table 5 provide support for the partial mediation of all three hypotheses because psychological safety has direct significant effect on operational productivity (c' = 0.30*). Thus, psychological safety affects operational productivity both directly and indirectly through the individual mediations of employee-led process improvement (H1→$a_1.b_1 = 0.11$*) and data driven digital transformation (H2→$a_1.b_2 = 0.24$*). The serial mediation of both employees led process improvement and data driven digital transformation (H3→$a_1.b_{12}b_2 = 0.05$*) for the relationship between psychological safety and operational productivity was also statistically significant. The total indirect effect of psychological safety on operational productivity ($a_1.b_1+a_1.b_2+a_1.b_{12}.b_2$) was a combination of the three hypothesised specific indirect effects and it was statistically significant at 0.40*. Next, we explain the theoretical and practice implications of these empirical findings.

5. Discussion

The original socio-cognitive conceptualisation and empirical testing of the antecedents for data driven digital transformation and operational productivity makes following important theoretical contributions and practice implications.

5.1. Theoretical implications

The first and most important theoretical contribution we make is that we delineate the specific mechanisms through which people related factors affect organisational attainments relevant to operations management in this digital age. Both process improvements and data driven digital transformations are widely recognised as socio-technical phenomena (see Narayanan et al. (2022) and Teubner and Stockhinger (2020)). There is, however, not enough clarity on the specifics of how the social factors affect either the process improvement or data driven digital transformation. Prior literature has explained operational improvements and employees' self-efficacy through the direct effects of psychological safety (Yang et al., 2017). We, however, provide additional detail to this socio-cognitive explanation by linking employees' psychological safety to operational productivity through the individual and serial mediations of employee-led process improvement and data-driven digital transformation. The empirical findings that psychological safety affects operational productivity both directly and

Table 4
Direct effect result.

	Consequent Variables								
	M1 = = Employees Led Process Improvement (PI)			M2 = Data Driven Digital Transformation (DT)			Y = Operational Productivity (OP)		
	Coeff.	SE	p-value	Coeff.	SE	p-value	Coeff.	SE	p-value
Control Variable = Hospital Size	0.15	(0.06)	n.s	0.01	(0.05)	n.s	0.07	(0.04)	n.s
Direct Effects									
X = Psychological Safety (PS)	0.71	(0.06)	***	0.65	(0.07)	***	0.30	(0.07)	***
$\mathbf{M_1}$ = Employee-Led Process Improvement (PI)				0.19	(0.06)	***	0.15	(0.05)	**
$\mathbf{M_2}$ = Data Driven Digital Transformation (DT)							0.37	(0.07)	***
Model Summary									
F-Value	105.20			106.70			63.46		
R^2	0.54			0.64			0.59		
p-value	***			***			***		

Table 5
Mediation analyses and hypotheses result.

Mediation Hypothesis	Direct Effect	Indirect Effect					
H1 - PS→PI→OP	c' = PS→OP 0.30***	a_1 = PS→PI 0.71***	b_1 = PI→OP 0.15**		$a_1.b_1$ 0.11[a]	LLCI 0.01	ULCI 0.24
H2 - PS→DT→OP	c' = PS→OP 0.30***	a_2 = PS→DT 0.65***	b_2 = DT→OP 0.37**		$a_1.b_2$ 0.24[a]	LLCI 0.11	ULCI 0.40
H3 - PS→PI→DT→OP	c' = PS→OP 0.30***	a_1 = PS→PI 0.71***	b_{12} = PI→DT 0.19**	b_2 = DT→OP 0.37***	$a_1.b_{21}.b_2$ 0.05[a]	LLCI 0.01	ULCI 0.11
			Effect	**SE**	**p-value**	**LLCI**	**ULCI**
Total Indirect Effect PS→OP	= ($a_1.b_1$ + $a_2.b_2$ + $a_1.b_{12}.b_2$)		0.40	(0.09)	***	0.24	0.58
Total Direct Effect PS→OP	= c'		0.30	(0.07)	***	0.01	0.10

***< 0.005, **< 0.05, [n.s] = not significant, Standardised Coeff. Are reported. SE = Standard Error, LC & UC CI = Lower and Upper Control Confidence Intervals @95%. PS=Psychological Safety, PI = Employee-Led Process Improvement, DT = Data Driven Digital Transformation, OP=Operational Productivity).
[a] All indirect effects are statistically significant because bootstrap confidence interval is entirely above zero, a_n b_n d_{mn} are path coefficients from Fig. 1.

indirectly through multiple mediations establish the psychological functioning of employees as a critical antecedent of operations performance. This is a new perspective in the operations and supply chain literature which brings it closer to the broader human resource and organisational behaviour literature that understands the significance of psychological safety and actively researches avenues to cultivate it within a work setting. Thus, the socio-cognitive theorisation employed in this research puts the spotlight on the employees' psychological functioning as an explanation of contemporary operational performance in this digital age which is a new and significant contribution to the discipline.

The second contribution of this study lies in establishing employee-led process improvement as an intervening step between psychologically safety and operational productivity. The socio-technical conceptualisation of process improvements in the operations management literature suggest that the social interactions within a work setting contribute to an organisational culture that facilitates employees' empowerment to initiate process improvement efforts (Malik and Abdallah, 2020). The empirical finding that a psychologically safe work environment makes employees feel confident in expressing their opinions and taking risks, thus, ensuring an active engagement with the process improvement efforts is a more nuanced explanation of how a social environment affects operations performance. This extends the assertions from the broader literature that psychological safety facilitates innovation through experimentation (Newman et al., 2017) to an operations context. This unique perspective on 'people-process interactions' provides new evidence that employees cognitions influence operational efficiency and effectiveness through reduced errors, minimised waste, and lowered overhead costs. The socio-cognitive theorisation of psychological safety as an antecedent mechanism also contributes to the theoretical underpinnings of psychological safety because prior literature had explained social exchange between employees and organisation as an intermediate step between psychological safety and performance (Mehmood et al., 2022; Newman et al., 2017). The mediation effect of human behaviour (employee-led process improvement) for the relationship between human cognition (psychological safety) and organisational attainment (operational productivity) was motivated by the triadic interactions of socio-cognitive theory. Therefore, the empirical evidence to this effect constitutes a new theoretical justification for conceptualising psychological safety as the driving mechanism for facilitating performance through employees' behaviour.

The empirical support for employees' cognitions as an antecedent of data-driven digital transformation to improve operational productivity is the third contribution this study makes. The socio-technical conceptualisation of digital transformation suggests a technical component of digital technology and infrastructure to generate big data and a social component comprising the organisational factors and peoples' skills and knowledge for generating useful insights from big data (Mikalef et al., 2019). The emerging discourse on the antecedents to successful digital transformation is suggesting that full benefits are materialised when digital technologies are made infrastructural through interactions with social and institutional processes (Teubner and Stockhinger, 2020). The socio-cognitive theorisation in this research provides empirical evidence to this effect by showing that employees' psychological safety, which is a function of the institutional environment, is the driving mechanism for operational productivity through data driven digital transformation. Furthermore, the literature also suggests 'cognition renewal' as a pre-requisite for digital transformations because the traditional way of organising is no more valid (Li et al., 2018). This also requires experimentation. thus, a psychologically safe workforce is likely to experiment with greater freedom for organisational learning (Edmondson and Lei, 2014; Mehmood et al., 2022). This organisational learning stemming from psychological safety and influencing both data-driven digital transformation and operational productivity constitutes a new explanation for improved operations performance in the extant literature.

The empirical support for the serial mediation of employee-led process improvement and data-driven digital transformation (H3) for the relationship between psychological safety and operational productivity is the fourth contribution of this research. The individual mediations (H1 and H2) provided evidence on how employees led process improvement and data driven digital transformation constitute separate intermediate steps between psychological safety and operational productivity. The literature on the effective utilisation of digital technologies, however, is suggesting an interplay between people and technology as a necessary condition (Teubner and Stockhinger, 2020). The triadic interactions of socio-cognitive theory (Bandura, 2001) enabled us to theorise this 'people-technology interplay' by positing that human cognition (psychological safety) leads to human behaviours (employee-led process improvement) affecting data-driven digital transformation as one of the organisational attainments examined in this research. Furthermore, the literature examining the digital transformation of operations and supply chain is suggesting a variety of ways through which predictive analytics and data-driven decision making may affect operations performance in this digital age (Dubey et al., 2022; Papanagnou et al., 2022). The empirical evidence we have provided affirms these theoretical assertions that employees' mutual cognitions are an important factor in shaping individual and organisational behaviour. Therefore, the conceptualisation and empirical testing for the serial mediation of employee-led process improvement and data-driven digital transformation for the relationship between psychological safety and operational productivity is a novel contribution to the academic discourse on digital transformation of operations and supply chains.

5.2. Managerial implications

The below expectations results of digital transformations within the industry have sparked significant interest among practitioners in uncovering the key success factors for such transformations (Forth et al. (2021). The literature highlights two overarching patterns that illustrate how industry approaches often fail to fully realise the intended benefits of digital transformation. First, there is a tendency in the industry to view digital technologies as the sole solution to industry problems (Hussain and Malik, 2022) with scant attention to the people-technology interactions that affect digital transformations. Second, the locus of social agency is commonly assumed to reside with management, where factors such as leadership commitment and support are regarded as primary social elements contributing to digital transformations (Forth et al. (2021). The empirical support for the socio-cognitive theorisation employed in this research addresses both these apparent limitations by providing unique insights. These insights advocate for a paradigm shift because this research positions employees as key stakeholders in digital transformations. It demonstrates that their cognitions and behaviour significantly impact both data-driven digital transformations and operational productivity. Thus, the onus is on the management to provide a social environment that cultivates psychological safety with implications for organisational attainments. The three-mediation hypotheses also constitute three different pathways through which psychological safety affects operational productivity. This informs practice on how to leverage constrained organisational resources. For example, H1 shows that psychological safety contributes to operational productivity through employees-led process improvement. The empirical support for H2 links psychological safety to operational productivity through data-driven data digital transformation. Thus, the practitioners may benefit from this finding by implementing a stepwise approach to improving operational productivity by prioritising a more efficient utilisation of their scarce resources. The serial mediation in H3, however, suggests that the total effects of psychological safety is maximised on operational productivity when both employees-led process improvement and data-driven digital transformation are implemented.

6. Conclusion. Limitations and future research directions

This research provides an explanation on why and how the interactions of 'people and technology' influence operational productivity. We do this by drawing on the socio-cognitive theory to examine how employees' cognitions (psychological safety) shape individual behaviours (employee-led process improvement) to affect organisational attainments such as data-driven digital transformations and operational productivity. A theoretical framework linking psychological safety to operational productivity through individual and serial mediations of 'employee-led process improvement' and 'data-driven digital transformation' is statistically tested. The results indicate that when employees' perceptions of interpersonal risks are allayed (psychological safety), it has a significant positive effect on operational productivity directly and indirectly through the individual and serial mediations of employee-led process improvement and data-driven digital transformations. The socio-cognitive theorisation of psychological safety as the driving mechanism that facilitates employee-led process improvement, data-driven digital transformation and operational productivity is a first in the academic literature with implications for both theory and practice.

Despite our best efforts to conduct a theoretically informed and methodologically rigorous study, we would like to acknowledge following limitations of our work which we suggest as future research directions. First, the triadic interactions suggested by the socio-cognitive theory are potentially reciprocal, but the positivist philosophical foundations employed in this research allowed us to consider the linear relationships between social environment, human cognitions and behaviours and organisational attainments. This allowed us to obtain generalisable patterns of theoretical relationships which was the overarching objective of our study. The socio-cognitive theorisation also provides a fertile opportunity to explicate a rich narrative of triadic reciprocal interactions (at the expense of generalisability) for the digital transformation of operations and supply chain which we suggest as future research. Second, the complex mediation analyses focus of this research meant that the boundary conditions of the established relationships were not pursued. We suggest an exploration and empirical testing of relevant contingencies for the mediations observed in this study as a future research direction.

CRediT authorship contribution statement

Mohsin Malik: Conceptualization, Formal analysis, Investigation, Methodology, Software, Validation, Writing – original draft. **Amir Andargoli:** Conceptualization, Data curation, Funding acquisition, Investigation, Project administration, Validation, Writing – review & editing. **Imran Ali:** Conceptualization, Validation, Writing – review & editing. **Roberto Chavez:** Writing – review & editing.

Data availability

The authors do not have permission to share data.

References

Al-Qubaisi, S.S., Ajmal, M., 2018. Determinants of operational efficiency in the oil and gas sector: a Balanced scorecards perspective. Benchmark Int. J. 25, 3357–3385.

Alkhaldi, R.Z., Abdallah, A.B., 2019. Lean management and operational performance in health care: implications for business performance in private hospitals. Int. J. Prod. Perform. Manag. 69, 1–21.

AlNuaimi, B.K., Khan, M., Ajmal, M.M., 2021. The role of big data analytics capabilities in greening e-procurement: a higher order PLS-SEM analysis. Technol. Forecast. Soc. Change 169, 120808.

AlNuaimi, B.K., Singh, S.K., Ren, S., Budhwar, P., Vorobyev, D., 2022. Mastering digital transformation: the nexus between leadership, agility, and digital strategy. J. Bus. Res. 145, 636–648.

Baer, M., Frese, M., 2003. Innovation is not enough: climates for initiative and psychological safety, process innovations, and firm performance. J. Organ. Behav. 24, 45–68.

Bandura, A., 1988. Organisational applications of social cognitive theory. Aust. J. Manag. 13, 275–302.

Bandura, A., 2001. Social cognitive theory: an agentic perspective. Annu. Rev. Psychol. 52, 1–26.

Battistoni, E., Gitto, S., Murgia, G., Campisi, D., 2023. Adoption paths of digital transformation in manufacturing SME. Int. J. Prod. Econ. 255, 108675.

Chavez, R., Malik, M., Ghaderi, H., Yu, W., 2022. Environmental collaboration with suppliers and cost performance: exploring the contingency role of digital orientation from a circular economy perspective. Int. J. Oper. Prod. Manag. 43 (4), 651–675.

Choo, A.S., Linderman, K.W., Schroeder, R.G., 2007. Method and psychological effects on learning behaviors and knowledge creation in quality improvement projects. Manag. Sci. 53, 437–450.

Cullinane, S.-J., Bosak, J., Flood, P.C., Demerouti, E., 2014. Job design under lean manufacturing and the quality of working life: a job demands and resources perspective. Int. J. Hum. Resour. Manag. 25, 2996–3015.

Dubey, R., Bryde, D.J., Dwivedi, Y.K., Graham, G., Foropon, C., 2022. Impact of artificial intelligence-driven big data analytics culture on agility and resilience in humanitarian supply chain: a practice-based view. Int. J. Prod. Econ. 250, 108618.

Edmondson, A., 1999. Psychological safety and learning behavior in work teams. Adm. Sci. Q. 44, 350–383.

Edmondson, A.C., Lei, Z., 2014. Psychological safety: the history, renaissance, and future of an interpersonal construct. Annu. Rev. Organ. Psychol. Organ. Behav. 1, 23–43.

Forth, P., Laubier, R., Chakraborty, S., Charanya, T., 2022. What the Data Tells Us about Digital Transformation, by Industry. BCG Publications, Boston Consulting Group.

Forth, P., Laubier, R., Chakraborty, S., Charanya, T., Magagnoli, M., 2021. Performance and Innovation Are the Rewards of Digital Transformation. BCG Publications, Boston Consulting Group.

Günther, W.A., Mehrizi, M.H.R., Huysman, M., Feldberg, F., 2017. Debating big data: a literature review on realizing value from big data. J. Strat. Inf. Syst. 26, 191–209.

Gupta, S., Drave, V.A., Dwivedi, Y.K., Baabdullah, A.M., Ismagilova, E., 2020. Achieving superior organizational performance via big data predictive analytics: a dynamic capability view. Ind. Market. Manag. 90, 581–592.

Hair, J.F., Babin, B.J., Anderson, R.E., 2018. Multivariate Data Analysis. Cengage, Mason. UNITED STATES, OH.

Hanelt, A., Bohnsack, R., Marz, D., Antunes Marante, C., 2021. A systematic review of the literature on digital transformation: insights and implications for strategy and organizational change. J. Manag. Stud. 58, 1159–1197.

Hayes, A.F., 2017. Introduction to mediation, moderation, and conditional process analysis: A regression-based approach. Guilford publications.

Holmström, J., Holweg, M., Lawson, B., Pil, F.K., Wagner, S.M., 2019. The Digitalization of Operations and Supply Chain Management: Theoretical and Methodological Implications. Wiley Online Library, pp. 728–734.

Hulland, J., Baumgartner, H., Smith, K.M., 2018. Marketing survey research best practices: evidence and recommendations from a review of JAMS articles. J. Acad. Market. Sci. 46, 92–108.

Huo, M.L., Boxall, P., 2018. Are all aspects of lean production bad for workers? An analysis of how problem-solving demands affect employee well-being. Hum. Resour. Manag. J. 28, 569–584.

Hussain, M., Ajmal, M., Subramanian, G., Khan, M., Anas, S., 2023. Challenges of big data analytics for sustainable supply chains in healthcare–a resource-based view. Benchmark Int. J. ahead-of-print.

Hussain, M., Malik, M., 2022. How do dynamic capabilities enable hotels to be agile and resilient? A mediation and moderation analysis. Int. J. Hospit. Manag. 106, 103266.

Jafari, H., Ghaderi, H., Malik, M., Bernardes, E., 2022. The effects of supply chain flexibility on customer responsiveness: the moderating role of innovation orientation. Prod. Plann. Control 1–19.

Khan, M., Ajmal, M.M., Jabeen, F., Talwar, S., Dhir, A., 2023. Green supply chain management in manufacturing firms: a resource-based viewpoint. Bus. Strat. Environ. 32, 1603–1618.

Le, T.T., 2023. The association of corporate social responsibility and sustainable consumption and production patterns: the mediating role of green supply chain management. J. Clean. Prod. 414, 137435.

Lee, B.W., Nittala, L., Jacobs, M.A., Yu, W., 2023. Impact of psychological safety on supply chain operational performance. Int. J. Prod. Res. 61, 754–773.

Lee, J.Y., Swink, M., Pandejpong, T., 2011. The roles of worker expertise, information sharing quality, and psychological safety in manufacturing process innovation: an intellectual capital perspective. Prod. Oper. Manag. 20, 556–570.

Li, F., 2020. Leading digital transformation: three emerging approaches for managing the transition. Int. J. Oper. Prod. Manag. 40, 809–817.

Li, L., Su, F., Zhang, W., Mao, J.Y., 2018. Digital transformation by SME entrepreneurs: a capability perspective. Inf. Syst. J. 28, 1129–1157.

Lin, S., Lin, J., Han, F., Luo, X., 2022. How big data analytics enables the alliance relationship stability of contract farming in the age of digital transformation. Inf. Manag. 59, 103680.

Malik, M., Abdallah, S., 2020. The relationship between organizational attitude and lean practices: an organizational sense-making perspective. Ind. Manag. Data Syst. 120, 1715–1731.

Malik, M., Andargoli, A., Chavez Clavijo, R., Mikalef, P., 2024. A relational view of how social capital contributes to effective digital transformation outcomes. J. Strat. Inf. Syst. 33, 101837.

Mehmood, M.S., Jian, Z., Akram, U., Akram, Z., Tanveer, Y., 2022. Entrepreneurial leadership and team creativity: the roles of team psychological safety and knowledge sharing. Person. Rev. 51, 2404–2425.

Mikalef, P., Boura, M., Lekakos, G., Krogstie, J., 2019. Big data analytics capabilities and innovation: the mediating role of dynamic capabilities and moderating effect of the environment. Br. J. Manag. 30, 272–298.

Mikalef, P., Krogstie, J., 2020. Examining the interplay between big data analytics and contextual factors in driving process innovation capabilities. Eur. J. Inf. Syst. 29, 260–287.

Möldner, A.K., Garza-Reyes, J.A., Kumar, V., 2020. Exploring lean manufacturing practices' influence on process innovation performance. J. Bus. Res. 106, 233–249.

Narayanan, S., Vickery, S.K., Nicolae, M.L., Castel, M.J., McLeod, M.K., 2022. The effects of lean implementation on hospital financial performance. Decis. Sci. J. 53, 557–577.

Nasiri, M., Saunila, M., Ukko, J., 2022. Digital orientation, digital maturity, and digital intensity: determinants of financial success in digital transformation settings. Int. J. Oper. Prod. Manag. 42, 274–298.

Nembhard, I.M., Edmondson, A.C., 2006. Making it safe: the effects of leader inclusiveness and professional status on psychological safety and improvement efforts in health care teams. J. Organ. Behav.: The International Journal of Industrial, Occupational and Organizational Psychology and Behavior 27, 941–966.

Newman, A., Donohue, R., Eva, N., 2017. Psychological safety: a systematic review of the literature. Hum. Resour. Manag. Rev. 27, 521–535.

Ong, C.H., Koo, Y.Y., Tan, O.K., Goh, C.F., 2021. Does rational culture matter in the relationship between lean manufacturing practices and operational productivity? J. Manuf. Technol. Manag. 32, 994–1015.

Papanagnou, C., Seiler, A., Spanaki, K., Papadopoulos, T., Bourlakis, M., 2022. Data-driven digital transformation for emergency situations: the case of the UK retail sector. Int. J. Prod. Econ. 250, 108628.

Paré, G., Guillemette, M.G., Raymond, L., 2020. IT centrality, IT management model, and contribution of the IT function to organizational performance: a study in Canadian hospitals. Inf. Manag. 57, 103198.

Schunk, D.H., DiBenedetto, M.K., 2020. Motivation and social cognitive theory. Contemp. Educ. Psychol. 60, 101832.

Shah, R., Ward, P.T., 2003. Lean manufacturing: context, practice bundles, and performance. J. Oper. Manag. 21, 129–149.

Shah, R., Ward, P.T., 2007. Defining and developing measures of lean production. J. Oper. Manag. 25, 785–805.

Soper, D., 2016. A-priori sample size calculator for structural equation models [Computer software]. Version 4.0. https://www.danielsoper.com/statcalc/calculator.aspx?id=89).

Teubner, R.A., Stockhinger, J., 2020. Literature review: understanding information systems strategy in the digital age. J. Strat. Inf. Syst. 29, 101642.

Vial, G., 2019. Understanding digital transformation: a review and a research agenda. J. Strat. Inf. Syst. 28, 118–144.

Wei, F., Abbas, J., Alarifi, G., Zhang, Z., Adam, N.A., Queiroz, M.J.d., 2023. Role of green intellectual capital and top management commitment in organizational environmental performance and reputation: moderating role of pro-environmental behavior. J. Clean. Prod. 405, 136847.

Westland, J.C., 2010. Lower bounds on sample size in structural equation modeling. Electron. Commer. Res. Appl. 9, 476–487.

Wood, R., Bandura, A., 1989. Social cognitive theory of organizational management. Acad. Manag. Rev. 14, 361–384.

Wu, C., Yao, H., Ning, X., Wang, L., 2021. Emergence of informal safety leadership: a social–cognitive process for accident prevention. Prod. Oper. Manag. 30, 4288–4305.

Yang, Y., Lee, P.K.C., Cheng, T.C.E., 2017. Leveraging selected operational improvement practices to achieve both efficiency and creativity: a multi-level study in frontline service operations. Int. J. Prod. Econ. 191, 298–310.