RECONSIDERING INDIVIDUALS’ COMPETENCIES IN BUSINESS INTELLIGENCE AND BUSINESS ANALYTICS TOWARD PROCESS EFFECTIVENESS: MEDIATION-MODERATION MODEL

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Abstract. The purpose of this study is to investigate the impact of individuals’ competencies in business intelligence (BI) and analytics (BA) on process effectiveness (PE). Moreover, to investigate the mediating role of user participation (UP) and the moderating role of gender in this relationship. An empirical analysis based on survey data was conducted. A sample of 215 middle and upper management levels from SMEs located in Jordan was surveyed to collect the data. Structural equation modelling through partial least squares-multi group analysis (PLS-MGA) is used to analyze the data. The results support the direct positive impact of individuals’ competencies in business intelligence (BA) and business analytics (BA). Moreover, user participation has been found to mediate this relationship. Additionally, the results showed that gender moderates the relationship between individuals’ competencies in business intelligence (BI) and analytics (BA) on process effectiveness (PE). The findings improve the understanding of the needed individuals’ competencies in business intelligence (BI) and analytics (BA) that affect process effectiveness (PE). This will help develop and arrange strategies that increase individuals’ competencies in business intelligence (BI) and analytics (BA) among employees. Furthermore, managers and owners should put plans for strategies to augment confidence amongst female employees.

Keywords: business intelligence (BI), business analytics (BA), process effectiveness (PE), user participation (UP).

JEL Classification: M12, M14, M19.

Introduction

Business intelligence (BI) is considered a response to recent requests regarding the precise, rapid, and soft entry to appropriate information throughout heavy usage of information technology, allowing the decision-makers to formulate superior enlightened decisions in a diversity of organizational frameworks (Sahay & Ranjan, 2008; Petrini & Pozzebon, 2009; Foshay & Kuziemsky, 2014; Arnett et al., 2017; Popović et al., 2019; Borissova et al., 2020; Hamad et al., 2021). Due to the augmented significance of effectiveness and efficiency of information analysis and the decision-making process at all levels, the strategic, tactical, and operational BI is turn out to be more widespread in the business context (Sangari & Razmi, 2015). Similarly, business analytics (BA) and its effect on process performance have also gained intensive attention from scholars and managers as well, in different areas such as customers and market processes, production, individual management, and the systems of performance management (Aydiner et al., 2019; Bronzo et al., 2013; Duan et al., 2020; Trkman et al., 2010).

The momentum usage of BA causes a considerable change in how business processes are viewed in organizations. Progressively, organizations must retain the capability to continuously rebuild procedures and remove neglected and ineffective processes, implementing activities that are extra effective and well associated with the organization’s goals. The competency of producing innovation creates value that is strictly related to the notion of absorptive capacity as well as energetic competencies (Teece et al., 1997; Davenport, 2006; Davenport & Harris, 2017). There is a vast consensus among scholars, managers and decision-makers that investing in the BA factors is continuously and progressively rising recently. In contrast, billions of dollars have been spent on these means through different types of businesses. These means are becoming the main priority of expense-worthy means and applications, particularly among medium and high-level managers (Cosic et al., 2015; Kristoffersen et al., 2021; Mikalef et al., 2018).

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Moreover, numerous features of BI and BA differentiate them from other organization-level technologies and impact the construction of BI and BA competencies. In that BA primarily involve the administrative user; therefore, it might need various endeavours to produce an acceptance for the usage of both BI and BA. In addition, this usage is mainly optional; as a result, users might need to truly realize the advantages of using them, generating demand for uncommon motivations for the use of BI and BA (Popović et al., 2012, 2014; Wang & Byrd, 2019).

Generally speaking, BI and BA are both of the furthest broadly investigated notions and interests fields on both levels industrially, and managerially (Işık et al., 2013; Ransbotham et al., 2016). Accordingly, BI and BA are vital and crucial in attaining effectiveness from different perspectives (Cao et al., 2015; Ramakrishnan et al., 2016). Accordingly, the current paper is responding to the call for more investigations on the individuals’ competencies in BI and BA on process effectiveness (PE). Also, it focuses on the mediating role of user participation (UP) and moderating role of gender in this relationship. Whereas previous research has investigated the aspects that impact technologies tools, attention has been paid to how individual demographic variances influence implementation. It is reasonable to consider that variances regarding demographic variables (e.g., age, gender, income, position and education) are vital to attitude formation and behaviour of BI and BA competencies (Chawla & Joshi, 2020).

The current research derived its importance from the fact that has recently grabbed the attention of executives and decision-makers due to their capacity to deliver complicated and competitive information inputs for the decision process (Ain et al., 2019). In addition, companies want to use BA resources to stay competitive (Bedley et al., 2018). Moreover, a vast number of studies have been conducted regarding BI and BA competencies from different perspectives for example, health care (Wang et al., 2018); accounting (Appelbaum et al., 2017); top management and development (Kulkarni et al., 2017); business value (Krishnamoorthi & Mathew, 2018); effect on decision-making (Niu et al., 2021); strategic impact (Tripathi et al., 2020); and organizational performance (Ramakrishnan et al., 2020). However, to the best knowledge of the authors, the current study is one of the rare studies that deliberate the individuals’ competencies of business intelligence (BI) and analytics (BA) impact process effectiveness (PE), as well as deliberating the mediating role of user participation (UP), and the moderating role of gender. Nevertheless, the current study bridging the gap in the literature, is that, there is a call for more investigations in the field of BI (El-Adaileh & Foster, 2019) and BA (Vidgen et al., 2017), particularly, in the context of MEs in Jordan (Ghatasheh et al., 2020).

1. Literature review and hypotheses development

1.1. BI, BA and PE

The current study built a hypothesized model based on the resource-based view (RBV) and information processing view (IPV). The RBV is possibly the most effective framework in management strategies extensively utilized to comprehend effectiveness and competitive advantage. RBV depicts the organization as an exclusive group of resources (tangible and intangible assets). Also, it proposes that maintaining competitive advantage and superior management strategy develop such resources that are essential, unique, not easy to imitate, and not exchangeable (Barney, 1991; Barney et al., 2001; Nandi et al., 2020; Pee & Kankanhalli, 2016; Verona, 1999). While, from an information processing view (IPV), numerous previous researches claim that BI and BA preserved as helping organizations in processing gigantic quantities of data to obtain profound perceptions. Consequently, they can convert this data to organizational knowledge and applicable decisions (Cao et al., 2015; Galbraith, 1965; Premkumar et al., 2005; Trieu, 2017).

Further, a BI success pattern has been established, which suggests that application aspects such as resilient management encouragement, a noticeable business hero, adequate resources, successful user contribution, suitable technical group abilities, and quality of data source system are all function optimistically affect application success from three viewpoints: organizational, enterprise and technical. This reflects the idea that BI is not an information technology implementation in the conventional meaning; instead, it is a trigger of several implementations (Arnott et al., 2017; Borissova et al., 2020; Popović et al., 2012; Wixom & Watson, 2001). Similarly, it has been argued that successful BI implementation needs particular competencies such as elevated data quality, suitable user gate and efficient incorporation with more systems (Işık et al., 2012; Okkonen et al., 2002; Ramakrishnan et al., 2020, 2016; Sangari & Razmi, 2015).

On the one hand, managerially, BI is considered a systematized and organized course of obtaining, incorporating, scrutinizing, and distributing information from two internal and external sources that are substantial for disclosing the dimensions of strategic business and for the process. On the other hand, BI, from the technical view, is described as a group of instruments and technologies, for example, data storage, process of online analytics, data mining, analytic and reporting means that allow the collecting, documenting, retrieval, manipulation, and information analysis, and support improving decision-making process (Chen et al., 2012; Taylor et al., 2020). In general, BA offers information related to the changes in the environment of the organization. This makes the information applicable in both strategy formulation and enhancing thinking processes during the strategy implementation stage. Further, BI likewise offers information about effective strategy implementation (Kohtamäki & Farmer, 2017;
Popović et al., 2010; Tripathi et al., 2020; Wieder & Ossimitz, 2015).

While a unique BA competence can be created through the structures of existing BA technological and organizational resources, in this sense, two keys to BA competencies have been identified: rapid insight and widespread use; simultaneously, both are basic dimensions of BA resources since they are playing a significant role in expanding business value (Wixom & Watson, 2001; Popović et al., 2010; Cosic et al., 2015; Wang & Byrd, 2019). However, in order to genuinely comprehend the competency, the individuals who involve in the process, the individual and collective skills employees should own, and the behaviours they should involve in, whether on an individual or collective level for process implementation; as employees’ competencies found to be a vital resource of success and effectiveness (Wright et al., 2001; Clulow et al., 2007; Salman & Ganie, 2020). In fact, the individual competencies of employees were found to be a determinant of effectiveness (Wright et al., 1998), mediating the relationship between human resource development and effectiveness (Otoo, 2019); improving organizational effectiveness (Potnuru & Sahoo, 2016).

Based on the above arguments, it is hypothesized that:

H1: Individual Business intelligence competencies have a direct and positive impact on process effectiveness.

H2: Individual Business analytics competencies have a direct and positive impact on process effectiveness.

1.2. BA, BI and UP

More profoundly, BI reflected activities in which information regarding markets, customers, competitors, novel technologies, and expansive social tendencies is collected and analyzed. In turn, this enables the organizations to make better decisions (Gbosbal & Kim, 1986); this includes improvements in detecting the external business environment (Lönnqvist & Puhakka, 2006). However, this does not prevent using the internal source of information (Williams et al., 2010). At the same time, BA activities assess the organization state that reflects the degree to which users are fostered to gather and analyze data regarding their tasks (Viaene & Van den Bunder, 2011; Vidgen et al., 2017).

While, user participation reflects the behaviours, tasks, and actions that users or their representatives make throughout the process of development (Hartwick & Barki, 1994). Accordingly, three statistically distinguished aspects of user participation have been recognized and confirmed: comprehensive responsible, user-IS relationship, and practical activity. In that, comprehensive responsibility denotes user actions and tasks indicating overall leadership or accountability for developing the system. User-IS relationship denoting the improvement endeavour indicating user-IS communication and impact. Practical action denotes the particular tangible plan and implementation assignments achieved through users. Yet, the three aspects are expected to be empirically connected. Users involved in one group of participative behaviours are likewise expected to be involved in the other two groups of behaviours (Barki & Hartwick, 1994).

Moreover, user participation is proposed to impact the post-implementation and stance on the system. While, individuals who are energetic in the process of system development are extremely expected to develop persuasions that the system is essential and indivisible in the whole system, in addition to the sense that the system is beneficial. Parallel confirmation for this argument derives from the previous organizational behaviour literature as significant participation in vital work decisions has been observed to increase job involvement and job satisfaction (Aamodt, 2015; Riggio, 2017). Consequently, BI and BA competencies primarily involve the administrative user and allow individuals within the organization context to analyze the current and prospective situations toward better decision-making, resulting in superior performance generated through users’ efforts. Later, this engagement, as well as BI and BA tools and technologies will augment individual participation (Spears & Barki, 2010; Kulkarni et al., 2017; Otoo, 2019).

Based on the arguments and discussion above, it is hypothesized that:

H3: Individual Business intelligence competencies have a direct positive impact on user participation.

H4: Individual Business analytics competencies have a direct positive impact on user participation.

1.3. UP as a mediator

Accordingly, the current research builds the hypothesized model regarding mediation through arguments drawn mainly from the theoretical base delivered through the structurational model of technology (Orlikowski, 1992, 2000). In that, user participation denotes an assessment of users’ activities, depicting the level of individuals’ contribution in the early stages besides the continuous growth of BI practices (Kulkarni et al., 2017). Conventionally, user participation denotes the tasks and jobs that users and/or their delegates execute through information systems development. Characteristically, these are the numerous design-related behaviours and actions that the target users and/or their delegates execute during the conducing stages. Whereas in such studies, user participation is revealed to have caused systems that superior meet the needs of users, which further simply adequate to the users, which in turn, drive to better results and extra level of users’ satisfaction (Barki & Hartwick, 1994; Cheng et al., 2021; El-Adaileh & Foster, 2019; Hawking & Sellitto, 2010).

As mentioned above, BI and BA primarily include the administrative user; therefore, it might need several endeavours to produce an acceptance of its usage. In addition, this usage is commonly optional; as a result, users might need to truly realize the profits of employing it,
then a call for a different type of incentive of usage will be generated. Further, organizations mainly employ it for tactical purposes; reducing costs or increasing operational efficiency is not the main focus of BI and BA; rather, the main focus is on augmenting effectiveness and developing competitive advantages. Therefore, the tools through which management influences an organization’s BI and BA competencies are varied of those for developing competencies with other organization systems (Gbosbal & Kim, 1986; Orlikowski, 2000; Lönnqvist & Puhakka, 2006; Michalewicz et al., 2006; Williams et al., 2010; Howson et al., 2018; Sun et al., 2018; Niu et al., 2021).

Based on the above arguments, it is hypothesized that:

**H5:** User participation mediates the relationship between business intelligence and process effectiveness.

**H6:** User participation mediates the relationship between business analytics and process effectiveness.

### 1.4. Gender as a moderator

Demographics such as gender are a crucial moderator in user participation, particularly in technology tools usage, acceptance, and adoption (Burke, 2002; Chawla & Joshi, 2020; Goswami & Dutta, 2015; Sun & Zhang, 2006; Venkatesh et al., 2003). This implies that gender differences were found to be expected in different studies regarding the adoption, acceptance and usage of technology tools, intelligence and information systems. In that, the bulk of studies has been conducted regarding the role of gender differences in different fields such as online commerce (Zhang et al., 2014); the adoption of bank technology (Wan et al., 2005); internet banking (Amin et al., 2006); technology usage (Shin, 2009); personal innovativeness in information technology usage and BI (Liu et al., 2015); and attitude, BI and an Internet-based learning medium (Cheung & Lee, 2011).

In the work of Trauth et al. (2004), three theories clarify the under-representation of females in the information technology career. The fundamental standpoint divides gender based on the assumption that there are noteworthy ingrained variances among males and females. In comparison, the social construction viewpoint emphasizes the social construction of information technology as a domain for males. Later, another theory built on individual differences between females as they connect to the necessities and features of information technology jobs as well as the information technology workplace. Correspondingly, there are three main and critical gender differences in terms of user acceptance and participation in research. Nevertheless, it has been revealed that the decision-making process of females and males varies and that females and males are different regarding information management (Venkatesh & Morris, 2000). These differences are drivers to reconsider the role of gender in the relationship between BI and BA, and therefore the following hypotheses are formulated:

**H7a:** Gender moderates the relationship between business intelligence and process effectiveness.

**H7b:** Gender moderates the relationship between business analytics and process effectiveness.

### 1.5. UP and PE

The early work of Hunton and Price (1997) clarified that the pattern of user participation performance in the line of the procedural justice theory enhances many critical ingredients in an organizational context, such as insights into decision control, outcome satisfaction, as well as degrees of job process with parallel augments in decision input. As the process of improvement becomes further significant, efficiency is likewise augmented. The direction of process development and success might be effectively determined through user participation and input. Correspondingly, participation in the traditional function indicates that users’ engagement is required for building practically accurate and effective systems. Moreover, participation is thought to be a tool for completion; it might help deliver superior information on necessities, overwhelms resistance, and indorses scheme alternatives. The aim is to generate an enhanced system through effective processes that are expected to be utilized by likely users (Cavaye, 1995).

Moreover, it has been argued that when users have the opportunity to articulate their thoughts, predilections, and apprehensions, this offers users a feeling of control
throughout the improvement process and this makes the process more effective (Hunton & Beeler, 1997). Process effectiveness mainly depends on understanding the way of doing the tasks, jobs, and problem-solving. Users from inside the organization, who are profoundly aware and involved directly in such activities, are more capable of improving the work done to make the process more effective (Steers, 1976). In that, recognizing the main features of individuals that influence effectiveness needs esteem of knowledge and competencies, requirements and pendants, insights and anticipations, interactions and experience elements (Nadler & Tushman, 1980; Austin et al., 2006; Diochon & Anderson, 2009).

Based on the above discussion and arguments, it is hypothesized that:

\[ H_8: \text{User participation impacts positively and directly process effectiveness.} \]

The theoretical model and the hypothesized relationships among the study’s variables are represented in Figure 1.

2. Methods and procedures

2.1. Instrument and measurements

The current study investigates the relationship between BI, BA, and PE, and it aims at investigating the mediating role of UP in this relationship. In addition, this study considers gender as a moderator in the relationship between BI, BA and PE. To this end, a questionnaire survey has been developed based on reviewing the related literature. Whereas this survey contains five sections to measure the study’s variables on a five-point Likert scale as follows:

Demographics information: such as gender, tenure, age, and education.

Business Intelligence competencies: This variable is measured using thirteen items adopted from the work of Gartner Group’s BI reports related to BI competencies with (\( \alpha = 0.91 \), Table 2). This measurement has been recently considered dependable and widely used and discussed in several studies such as Hostmann et al. (2009), Işik et al. (2012), and Işik et al. (2013).

Business Analytics: Based on the purpose of the current study, measuring individual competencies regarding BA. While BA is concerned about using technological tools such as software, hardware and information management skills, this variable is measured using eight items (\( \alpha = 0.88 \), Table 2) derived and adopted from Cosic et al. (2012) and has been proven in terms of validity and reliability in the bulk of studies (Appelbaum et al., 2017; Cosic et al., 2015; Krishnamoorthi & Mathew, 2018; Santiago Rivera & Shanks, 2015; Wang et al., 2018).

User Participation: This section contains four items that were measured this variable (\( \alpha = 0.89 \), Table 2). These items were derived and adopted relying on previous studies (Barki & Hartwick, 1994; Guimaraes & Igbaria, 1997; McKeen & Guimaraes, 1997) and have been widely used as well as proven in terms of validity and reliability (Lin & Shao, 2000; Spears & Barki, 2010; Kulkarni et al., 2017).

Process Effectiveness: Fifteen items were used to measure this variable (\( \alpha = 0.86 \), Table 2). These items were derived from prior studies (Watson et al., 1995). Again, this scale has been used in many previous studies, making it reliable and valid (Chowdhury, 2005; Presbitero, 2021; Watson et al., 2003).

2.2. Sample and data collection

SMEs contribute significantly to social and economic growth in both developed and developing countries. Apart from fighting poverty and unemployment, they are regarded as a growth engine for the economy (Pandya, 2012). Moreover, 98% of registered companies in Jordan are SMEs type, 60% of formal jobs, and 50% of the GDP. The relevance of this industry resides in the constant hiring of people in Jordanian manufacturing SMEs (JYES, 2017). In addition, according to the Jordanian statistics department, almost 17,000 industrial institutions exist in Jordan, with nearly 98% being small and medium-sized businesses (Department of Statistics, 2020).

The data for the current study were gathered through an online form and sent to the participants. Participants were from middle and upper management levels and supervisors responsible for tasks and process accomplishments from Jordan’s small and medium manufacturing enterprises. Each of these respondents was in decision-making positions in their organizations, and they are aware of the variables used in the current study, such as BI, BA, UP and PE. Whereas a purposive sampling technique was used to choose those participants as it fits the aim of the study, in that, choosing people who are in charge and in a position that allows them to make decisions as well as they are familiar with different concepts that were used to accomplish this study (Etikan et al., 2016). Moreover, a statement of disclosure was comprised in the questionnaire to disclose the aim of data collection and guarantee the confidentiality of respondents’ feedback and data will be utilized just for academic purposes. Further, as recommended in the previous literature, questionnaire items were clear and simple, an overview of each variable was included to assure clarity of its concept, and polite reminders were sent after a few weeks to fill out the questionnaire, decreasing the nonresponse bias (Toepoel & Schonlau, 2017).

Two hundred and fifty-five (255) questionnaires were distributed to the approached sample, and the respondents voluntarily contributed to answering the questions involved in the survey. Two hundred and nineteen (219) questionnaires were retrieved, giving a response rate of approximately 86 per cent (86). However, two hundred and fifteen (215) questionnaires were valid for the analysis stage, and four (4) questionnaires were excluded due to inappropriate filling. Out of 215 respondents, 69 per cent were male, and 31 per cent were female. The respondents’ age categories were 21 per cent (25–34 years), 38 per cent (35–44 years), 28 per cent (45–54 years) and 13 per cent (45–54 years).
(55–64 years). The education levels were as: 33 per cent (Diploma and below), 45 per cent (Bachelor degree), 14 per cent (Master degree) and 8 per cent (PhD degree). Tenure also recoded as 9 per cent (1–4), 19 per cent (5–9 years), 36 per cent (10–14 years), 22 per cent (15–19 years) and 14 per cent were (≥ 20 years) Demographics information of the respondents provided in Table 1.

Table 1. Descriptive statistics of the sample

| Category   | Details         | Number | Per cent (%) |
|------------|-----------------|--------|--------------|
| Gender     | Male            | 149    | 69.3         |
|            | Female          | 66     | 30.7         |
| Age        | 25–34           | 45     | 21           |
|            | 35–44           | 82     | 38           |
|            | 45–54           | 60     | 28           |
|            | 55–63           | 28     | 13           |
| Education  | Diploma and below | 71    | 33           |
|            | Bachelor degree | 97     | 45           |
|            | Master degree   | 30     | 14           |
|            | PhD degree      | 17     | 8            |
| Tenure     | 1–4             | 20     | 9            |
|            | 5–9             | 41     | 19           |
|            | 10–14           | 77     | 36           |
|            | 15–19           | 47     | 22           |
|            | ≥ 20            | 30     | 14           |

2.3. Analysis

Structural equation modelling (SEM) was utilized in the current study as a standard reporting method to conduct accuracy and replicability. Whereas, partial least squares structural equation modelling (PLS-SEM) is used in numerous fields such as operation and international management (Peng & Lai, 2012; Richter et al., 2016), marketing and strategic management (Hair et al., 2017), human resource management (Ringle et al., 2020), information system (Urbach & Ahlemann, 2010), Knowledge management (Cepeda-Carrion et al., 2019), and organization and group research (Sosik et al., 2009). More precisely, various contemporary studies employed the PLS method to search results in SMEs, which in turn verifies the suitability of using this method for the current study (Naala et al., 2017; Ali et al., 2018; Schubert, 2021). Moreover, the justification for employing PLS-SEM contains PLS-SEM generates “a sole determinant mark for each SEM composite for each remark,” additionally, PLS-SEM correlates the overall variance explained with $R^2$ (Hair et al., 2017).

The current study employed the statistical tool SmartPLS 3 for analyzing the data measurement model. At the same time, tests were performed to, firstly, examine composite reliability (CR), average variance extracted (AVE), and Cronbach’s alpha (CA). Secondly, analyzing the theoretical model through examining discriminant validity (DV), besides testing common method bias (variance inflation factor (VIF)), $F^2$, $R^2$ (coefficient of determination), $Q^2$ (predictive relevance), and standardized root means square residual (SRMR). Finally, SEM was conducted to test the proposed hypotheses of the current study.

2.3.1. Measurement model

Although the scales that used in the current study have been utilized in several prior studies, as mentioned in section 2.1, and have been shown high degree in terms of validity and reliability; however, in the first stage of the analysis, CA was utilized to determine the reliability of the constructs adopted in the current study. The values of CA for all constructs showed high levels, in that BI with 0.910, BA with 0.880, UP with 0.890, and PE with 0.860. consequently, as recommended by Hair et al. (2017), the values met the threshold. Whereas Bagozzi and Yi (1988) and Hair et al. (2011) concluded that CR measures the internal consistency with the threshold of (≥ 0.70). Consequently, the results showed that the values of CR are: 0.90 for BI, 0.89 for BA, 0.91 for UP, and 0.87 for PE. Furthermore, the current study used AVE to assess convergent validity, and it has been suggested that the threshold of AVE value to be (≥ 0.50) (Fornell & Larcker, 2016). The analysis result of the current study showed that AVE values are: 0.87 for BI, 0.81 for BA, 0.73 for UP, and 0.67 for PE. These values are represented in Table 2. Finally, discriminant validity was assessed using the criterion of Fornell and Larcker (2016). They suggested that the AVE value for each latent scale should be higher than the latent scale’s highest squared correlation compared with any other latent scale. Table 3 shows the assessment values of DC, and it met the required criterion.

Table 2. Measurement model

| Construct | Code | Factor Loading | p-value | CR  | CA (α) | AVE  |
|-----------|------|----------------|---------|-----|--------|------|
| BI        | BI   | 0.823          | 0.000   | 0.90| 0.91   | 0.8703|
|           | BI   | 0.901          | 0.000   |     |        |      |
|           | BI   | 0.874          | 0.000   |     |        |      |
|           | BI   | 0.912          | 0.000   |     |        |      |
|           | BI   | 0.917          | 0.000   |     |        |      |
|           | BI   | 0.907          | 0.000   |     |        |      |
|           | BI   | 0.889          | 0.000   |     |        |      |
|           | BI   | 0.874          | 0.000   |     |        |      |
|           | BI   | 0.821          | 0.000   |     |        |      |
|           | BI   | 0.863          | 0.000   |     |        |      |
|           | BI   | 0.886          | 0.000   |     |        |      |
|           | BI   | 0.814          | 0.000   |     |        |      |
|           | BI   | 0.897          | 0.000   |     |        |      |
End of Table 2

Table 3. Assessing DC (Correlations between Latent Variables and Square Roots of AVE)

| Construct | Code | Factor Loading | p-value | CR | CA (α) | AVE |
|-----------|------|---------------|---------|----|--------|-----|
| BA        | BA 1 | 0.794         | 0.000   | 0.89| 0.88   | 0.8146 |
|           | BA 2 | 0.881         | 0.000   |     |        |      |
|           | BA 3 | 0.846         | 0.000   |     |        |      |
|           | BA 4 | 0.910         | 0.000   |     |        |      |
|           | BA 5 | 0.920         | 0.000   |     |        |      |
|           | BA 6 | 0.862         | 0.000   |     |        |      |
|           | BA 7 | 0.821         | 0.000   |     |        |      |
|           | BA 8 | 0.880         | 0.000   |     |        |      |
| UP        | UP 1 | 0.893         | 0.000   | 0.91| 0.89   | 0.7389 |
|           | UP 2 | 0.855         | 0.000   |     |        |      |
|           | UP 3 | 0.883         | 0.000   |     |        |      |
|           | UP 4 | 0.906         | 0.000   |     |        |      |
| PE        | PE 1 | 0.874         | 0.000   |     |        |      |
|           | PE 2 | 0.905         | 0.000   |     |        |      |
|           | PE 3 | 0.865         | 0.000   |     |        |      |
|           | PE 4 | 0.807         | 0.000   |     |        |      |
|           | PE 5 | 0.911         | 0.000   |     |        |      |
|           | PE 6 | 0.896         | 0.000   |     |        |      |
|           | PE 7 | 0.886         | 0.000   |     |        |      |
|           | PE 8 | 0.852         | 0.000   |     |        |      |
|           | PE 9 | 0.847         | 0.000   |     |        |      |
|           | PE 10| 0.866         | 0.000   |     |        |      |
|           | PE 11| 0.861         | 0.000   |     |        |      |
|           | PE 12| 0.889         | 0.000   |     |        |      |
|           | PE 13| 0.903         | 0.000   |     |        |      |
|           | PE 14| 0.917         | 0.000   |     |        |      |
|           | PE 15| 0.902         | 0.000   |     |        |      |

Table 4. Structural model

| Construct | $R^2$ | Adj. $R^2$ | $F^2$ | $Q^2$ | VIF | SRMR |
|-----------|-------|------------|-------|-------|-----|------|
| BI        | 0.412 | 0.410      | 0.094 | 0.301 | 2.844| 0.042|
| BA        | 0.648 | 0.650      | 0.421 | 0.342 | 2.012|      |
| UP        | 0.524 | 0.520      | 0.087 | 0.412 | 1.854|      |
| PE        | 0.068 | 0.882      |       |       |      |      |

2.3.3. Structural equation modelling (Multigroup analysis)

The results of PLS-SEM analysis revealed that BI has a direct positive and significant impact on PE with $\beta = 0.506$, $t = 5.841$, $p < 0.000$, which in turn, makes $H1$ supported. Moreover, the results showed that BA has a direct positive and significant impact on PE with $\beta = 0.408$, $t = 3.532$, $p < 0.000$, which makes $H2$ supported. Likewise, BI has a direct positive and significant impact on UP with $\beta = 0.534$, $t = 5.562$, $p < 0.000$, as a result $H3$ is supported.
Table 5. Hypotheses testing results

| Type of impact | Relationship | Hypothesis | β-value | t-value | p-value | Result |
|---------------|--------------|------------|---------|---------|---------|--------|
| Direct        | BI → PE      | H1         | 0.506   | 5.841   | 0.000*  | supported |
|               | BA → PE      | H2         | 0.408   | 3.532   | 0.000*  | supported |
|               | BI → UP      | H3         | 0.534   | 5.562   | 0.000*  | supported |
|               | BA → UP      | H4         | 0.505   | 5.328   | 0.000*  | supported |
|               | UP → PE      | H8         | 0.254   | 3.745   | 0.000*  | supported |
| Indirect      | Mediation    | BI → UP → PE | H5   | 0.512   | 5.344   | 0.000*  | supported |
|               | Mediation    | BA → PU → PE | H6   | 0.537   | 5.854   | 0.000*  | supported |
|               | Moderation   | BI → Gender → PE | H7a | 0.532   | 5.242   | 0.000*  | supported |
|               | Moderation   | BA → Gender → PE | H7b | 0.518   | 5.398   | 0.000*  | supported |

Note: *p-value < 0.001.

Further, BA has a direct positive and significant impact on UP with $\beta = 0.505$, $t = 5.328$, $p < 0.000$, also, $H4$ is supported. In addition, a mediation effect of UP on the relationship of BI and PE was detected with $\beta = 0.512$, $t = 5.344$, $p < 0.000$, this implies support for $H5$. Similarly, a mediation of UP on the relationship of BA and PE was detected with $\beta = 0.537$, $t = 5.854$, $p < 0.000$, this implies support for $H6$. A moderation effect is detected of gender on the relationship of BI and PE with $\beta = 0.532$, $t = 5.242$, $p < 0.000$, implying support for $H7a$. Also, a moderation effect is detected of gender on the relationship of BA and PE with $\beta = 0.518$, $t = 5.398$, $p < 0.000$, this implies support for $H7b$. Finally, UP has a direct positive and significant impact on PE with $\beta = 0.254$, $t = 3.745$, $p < 0.000$, which in turn, makes $H8$ supported. The analysis results are represented in Table 5.

Conclusions and discussion

The current study suggested a mediation-moderation model regarding the relationship between BI, BA, UP and PE, with UP as a mediator between BI and PE and between BA and PE. In addition, it proposed a moderating effect of gender in the relationship between BA, PE and BA, PE. As proposed and predicted in the model’s study, the analysis results showed the following findings: BI impacts directly and positively PE; BA impacts directly and positively PE; BI impacts directly and positively UP; BA impacts directly and positively UP; UP impacts directly and positively PE; UP mediates the relationship between, from one hand, BA and PE, on the other hand, UP mediates the relationship between BA and PE. Furthermore, gender moderates the relationship between BI and PE and moderates the relationship between BA and PE. Accordingly, our study confirms previous findings and asserts the importance of BI effectiveness (Gessner & Scott, 2009), particularly, in the Jordanian context (Masa’Deh et al., 2021). In the same vein, BA was found to be beneficial for PE as well, which makes our findings consistent with previous studies (Cao et al., 2015). However, UP has been identified as a mediator in the current study which, also, verifies the argument that UP is vital in such system development (Cavaye, 1995). Moreover, as the previous literature observed that there are different results regarding the role of gender on technology adoption (e.g. BI and BA) (Goswami & Dutta, 2015), which in turn, asserts our arguments and findings.

The current study has the following implications: first, theoretically, BI and BA are beneficial for PE, which makes our findings is a genuine attempt to distinguish individual BI and BA competencies from BI and BA systems on the organizational level. This differentiates the required capabilities and competencies regarding BI and BA levels, whether organizational or individual, as previous studies focus mainly, on organizational BI and BA capabilities and competencies that are substantial for the decision-making process (Hamad et al., 2021; İşik et al., 2012; Kulkarni et al., 2017; Lahrmann et al., 2011; Sangari & Razmi, 2015). Besides, the findings revealed an essential factor that enhances the power of using such competencies of managing acquired knowledge by individuals toward strengthening and leveraging the effectiveness (Watson et al., 1995; Spears & Barki, 2010; Otoo, 2019; Wang & Byrd, 2019). Further, the findings show differences in acquiring and utilizing BI and BA competencies. An increasing number of researches examining gender differences have confirmed the significance of recognizing the role of gender concerning information technology and knowledge in a diversity of frameworks (Cheung & Lee, 2011; Goswami & Dutta, 2015; Trauth et al., 2004; Venkatesh & Morris, 2000; Zhang et al., 2014).

Second, managerially, managers should be conscious that BI and competencies have distinct components and need individual attention. Additionally, managers need to know that the behaviours and tools to enhance these competencies are essential to the effectiveness and augmenting performance. Organizations need to hold a warehouse of precise, trustworthy, and harmonious information that is accessible at the appropriate level of detail through all of its entities. This information might be enhanced through an abundant of BI and BA competencies with function-
sorts of decision-makers (Lahrmann et al., 2011; Işık et al., 2012; Sangari & Razmi, 2015; Santiago Rivera & Shanks, 2015; Yeoh & Popović, 2016; Kulkarni et al., 2017; Brill, 2019; Hamad et al., 2021).

As the case in any research work, the current study has limitations that could guide future research. These limitations are: the current study is a cross-sectional type, while longitudinal studies are, indeed, needed to see the ability to identify and connect incidents to specific detections, as well as to describe these detections in terms of existence, timing and chronicity (Saunders et al., 2009). The current study was conducted in a developing context, Jordan, whereas even developing countries vary in different aspects. An attempt to re-conduct the same model is needed, whether in another developing country or comparing developing and developed countries. This study used a sample from SMEs; although SMEs play a vital role in most modern economies (Savlovšchi & Robu, 2011); however, different types of organizations to be studied may exhibit different results.

References

Aamodt, M. G. (2015). Industrial organizational psychology: An applied approach (6th ed.). Cengage Learning.

Ain, N., Vaia, G., DeLone, W. H., & Waheed, M. (2019). Two decades of research on business intelligence system adoption, utilization and success – A systematic literature review. Decision Support Systems, 125, 113113. https://doi.org/10.1016/j.dss.2019.113113

Ali, F., Rasoolimanesh, S. M., Sarstedt, M., Ringle, C. M., & Ryu, K. (2018). An assessment of the use of partial least squares structural equation modeling (PLS-SEM) in hospitality research. International Journal of Contemporary Hospitality Management, 30(1), 514–538. https://doi.org/10.1108/IJCHM-10-2016-0568

Amin, H., Hamid, M. R. A., Tanakinja, G. H., & Lada, S. (2006). Undergraduate attitudes and expectations for mobile banking. Journal of Internet Banking and Commerce, 11(3), 1–10.

Andersson, L. M., & Bateman, T. S. (1997). Cynicism in the workplace: Some causes and effects. Journal of Organizational Behavior, 18(5), 449–469. https://doi.org/10.1002/(SICI)1099-1579(19970918)18:5<449::AID-JOB808>3.0.CO;2-O

Appelbaum, D., Kogan, A., Vasaehrley, M., & Yan, Z. (2017). Impact of business analytics and enterprise systems on managerial accounting. International Journal of Accounting Information Systems, 25, 29–44. https://doi.org/10.1016/j.accinf.2017.03.003

Arnott, D., Lizama, F., & Song, Y. (2017). Patterns of business intelligence systems use in organizations. Decision Support Systems, 97, 58–68. https://doi.org/10.1016/j.dss.2017.03.005

Austin, J., Stevenson, H., & Wei-Skillern, J. (2006). Social and commercial entrepreneurship: Same, different, or both? Entrepreneurship Theory and Practice, 30(1), 1–22. https://doi.org/10.1111/j.1540-6520.2006.00107.x

Aydiner, A. S., Tatoglu, E., Bayraktar, E., Zaim, S., & Delen, D. (2019). Business analytics and firm performance: The mediating role of business process performance. Journal of Business Research, 96(November 2018), 228–237. https://doi.org/10.1016/j.jbusres.2018.11.028

Bagozzi, R. P., & Yi, Y. (1988). On the evaluation of structural equation models. Journal of the Academy of Marketing Science, 16(1), 74–94. https://doi.org/10.1007/BF02723327

Barki, H., & Hartwick, J. (1994). Measuring user participation, user involvement, and user attitude. MIS Quarterly, 18(1), 59–82. https://doi.org/10.2307/249610

Barney, J. (1991). Firm resources and sustained competitive advantage. Journal of Management, 17(1), 99–120. https://doi.org/10.1177/014920639101700108

Barney, J., Wright, M., & Ketchen, D. J. (2001). The resource-based view of the firm: Ten years after 1991. Journal of Management, 27(6), 625–641. https://doi.org/10.1177/014920630102700601

Bedley, R. T., Ghoshal, T., Iyer, L. S., & Bhadury, J. (2018). Business analytics and organizational value chains: A relational mapping. Journal of Computer Information Systems, 58(2), 151–161. https://doi.org/10.1080/08874417.2016.1220238

Borissova, D., Cvetkova, P., Garvanov, I., & Garvanova, M. (2020). A framework of business intelligence system for decision making in efficiency management. In K. Saeed & J. Dvirsksy (Eds), Computer Information Systems and Industrial Management. CIISIM 2020. Lecture Notes in Computer Science (Vol. 12133). Springer. https://doi.org/10.1007/978-3-030-47679-3_10

Brill, C. (2019). The influence of management support on the drivers of business intelligence success [Doctoral dissertation, University of Pretoria, March].

Bronzo, M., de Resende, P. T. V., de Oliveira, M. P. V., McCormack, K. P., de Sousa, P. R., & Ferreira, R. L. (2013). Improving performance aligning business analytics with process orientation. International Journal of Information Management, 33(2), 300–307. https://doi.org/10.1016/j.ijinfomgt.2012.11.011

Burke, R. R. (2002). Technology and the customer interface: What consumers want in the physical and virtual store. Journal of the Academy of Marketing Science, 30(4), 411–432. https://doi.org/10.1177/009207002236914

Cao, G., Duan, Y., & Li, G. (2015). Linking business analytics to decision making effectiveness: A Path model analysis. IEEE Transactions on Engineering Management, 62(3), 384–395. https://doi.org/10.1109/TEM.2015.2441875

Carranza, R., Díaz, E., Martín-Consuegra, D., & Fernández-Ferrín, P. (2020). PLS–SEM in business promotion strategies. A multigroup analysis of mobile coupon users using MICHOM. Industrial Management and Data Systems, 120(12), 2349–2374. https://doi.org/10.1108/IMDS-12-2019-0726

Cavaye, A. L. M. (1995). User participation in system development revisited. Information and Management, 28(5), 311–323. https://doi.org/10.1016/0378-7206(94)00053-L

Cepeda-Carrion, G., Cegarra-Navarro, J. G., & Cillo, V. (2019). Tips to use partial least squares structural equation modelling (PLS-SEM) in knowledge management. Journal of Knowledge Management, 23(1), 67–89. https://doi.org/10.1108/JKMM-05-2018-0322

Chawla, D., & Joshi, H. (2020). The moderating role of gender and age in the adoption of the mobile wallet. Foresight, 22(4), 483–504. https://doi.org/10.1108/FS-11-2019-0094

Chen, H., Chiang, R. H. L., Storey, V. C., & Robinson, J. M. (2012). Business intelligence research business intelligence and analytics: From Big Data to Big Impact. MIS Quarterly, 36(4), 1165–1188. https://doi.org/10.2307/4170350

Cheng, X., Su, L., Luo, X., Benitez, J., & Cai, S. (2021). The good, the bad, and the ugly: Impact of analytics and artificial intelligence-enabled personal information collection on privacy...
and participation in ridesharing. *European Journal of Information Systems*, 31(3), 339–363. https://doi.org/10.1080/0960085X.2020.1869508

Cheung, C. M. K., & Lee, M. K. O. (2011). Exploring the gender differences in student acceptance of an internet-based learning medium. In *Technology Acceptance in Education* (pp. 183–199). Sense Publishers. https://doi.org/10.1007/978-94-6091-487-4_10

Chowdhury, S. (2005). Demographic diversity for building an effective entrepreneurial team: Is it important? *Journal of Business Venturing*, 20(6), 727–746. https://doi.org/10.1016/j.jbusvent.2004.07.001

Chulow, V., Barry, C., & Gerstman, J. (2007). The resource-based view and value: The customer-based view of the firm. *Journal of European Industrial Training*, 31(1), 19–35. https://doi.org/10.1108/0309059070172178

Cosic, R., Shanks, G., & Maynard, S. (2012, 3–5 December). Towards a business analytics capability maturity model. In *ACIS 2012: Proceedings of the 23rd Australasian Conference on Information Systems* (pp. 1–11). Geelong. Cosic, Shanks & Maynard.

Cosic, R., Shanks, G., & Maynard, S. (2015). A business analytics capability framework. *Australasian Journal of Information Systems*, 19, S5–S19. https://doi.org/10.31277/ajis.v1960.1150

Davenport, T. H. (2006). Competing on analytics. *Harvard Business Review*, 84(1), 98–108.

Davenport, T., & Harris, J. (2017). *Competing on analytics: The new science of winning* (1st ed.). Harvard Business Press.

Department of Statistics. (2020). *Jordan in figures 2017*. http://dwsweb.dos.gov.jo/ar/

Dietrich, M., & Anderson, A. R. (2009). Social enterprise and effectiveness: A process typology. *Social Enterprise Journal*, 5(1), 7–29. https://doi.org/10.17508/1091065381

Duan, Y., Cao, G., & Edwards, J. S. (2020). Understanding the impact of business analytics on innovation. *European Journal of Operational Research*, 281(3). https://doi.org/10.1016/j.ejor.2018.06.021

El-Adaileh, N. A., & Foster, S. (2019). Successful business intelligence implementation: A systematic literature review. *Journal of Work–Applied Management*, 11(2), 121–132. https://doi.org/10.1108/JWAM-09-2019-0027

Etikan, I., Musa, S. A., & Alkassim, R. S. (2016). Comparison of convenience sampling and purposive sampling. *American Journal of Theoretical and Applied Statistics*, 5(1), 1–4. https://doi.org/10.11648/j.ajtas.20160501.11

Fornell, C., & Larcker, D. F. (2016). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39–50. https://doi.org/10.1177/0022247371810800104

Foshay, N., & Kuziemskey, C. (2014). Towards an implementation framework for business intelligence in healthcare. *International Journal of Information Management*, 34(1), 20–27. https://doi.org/10.1016/j.ijinformgmt.2013.09.003

Galbraith, J. R. (1965). Organization design: An information processing view. *Interfaces*, 4(3), 28–36. https://doi.org/10.1287/inte.4.3.28

Ghosbal, S., & Kim, S. K. (1986). Building effective intelligence systems for competitive advantage. *Sloan Management Review*, 28(1), 49–58.

Geisser, S. (1974). A predictive approach to the random effect model. *Biometrika*, 61(1), 1–7. https://doi.org/10.1093/biomet/61.1.101

Gessner, G., & Scott, R. A. (2009). Using business intelligence tools to help manage costs and effectiveness of business-to-busi-
Işık, Ö., Jones, M. C., & Sidorova, A. (2013). Business intelligence success: The roles of BI capabilities and decision environments. *Information and Management, 50*(1), 13–23. https://doi.org/10.1016/j.infoheic.2012.12.001

Işık, Ö., Sidorova, A., & Jones, M. C. (2012). Business intelligence success and the role of BI capabilities. *Intelligent Systems in Accounting, Finance and Management, 18*(January), 161–176. https://doi.org/10.1002/isa.329

Jordanian Young Economists Society. (2017). Challenges facing SMEs and what is needed to empower SMEs sector in Jordan. https://www.kas.de/documents/%20252038/253252/7_dokument_dok_pdf_41279_2_pdf/571a302c-7e84-7fdd-fa5b-72d2ecc44e85?version=1.0&hash=1539652585795

Kohtamäki, M., & Farmer, D. (2017). Strategic agility – integrating business intelligence with strategy. In M. Kohtamäki (Ed.), *Real-time strategy and business intelligence* (pp. 11–36). Palgrave Macmillan. https://doi.org/10.1007/978-3-319-54846-3

Krishnamoorti, S., & Mathew, S. K. (2018). Business analytics and business value: A comparative case study. *Information and Management, 55*(5), 643–666. https://doi.org/10.1016/j.infoheic.2018.01.005

Kristoffersen, E., Mikalef, P., Blomsmå, F., & Li, J. (2021). Towards a business analytics capability for the circular economy. *Technological Forecasting and Social Change, 171*, 120957. https://doi.org/10.1016/j.techfore.2021.120957

Kulkarni, U. R., Robles-Flores, J. A., & Popovič, A. (2017). Business intelligence capability: The effect of top management and the mediating roles of user participation and analytical decision making orientation. *Journal of the Association for Information Systems, 18*(7), 516–541. https://doi.org/10.17705/1aiss.00462

Lahrmann, G., Marx, F., Winter, R., & Wortmann, F. (2011). Business intelligence maturity: Development and evaluation of a theoretical model. In *The Proceedings of the Annual Hawaii International Conference on System Sciences, February*. IEEE. https://doi.org/10.1109/HICSS.2011.90

Lin, W. T., & Shao, B. B. M. (2000). The relationship between user participation and system success: A simultaneous contingency approach. *Information and Management, 37*(6), 283–295. https://doi.org/10.1016/S0378-7206(99)00055-5

Liu, F., Zhao, X., Chau, P. Y. K., & Tang, Q. (2015). Roles of perceived value and individual differences in the acceptance of mobile coupon applications. *Internet Research, 25*(3), 471–495. https://doi.org/10.1108/IntR-02-2014-0053

Lonnqvist, A., & Puhakka, V. (2006). The measurement of business intelligence. *Information Systems Management, 23*(1), 32–40. https://doi.org/10.1002/ism.369

Masa'Deh, R., Obeidat, Z., Maqableh, M., & Shah, M. (2021). The impact of business intelligence systems on an organization's effectiveness: The role of metadata quality from a developing country's view. *International Journal of Hospitality and Tourism Administration, 22*(1), 64–84. https://doi.org/10.1080/15256480.2018.1547239

McKeen, J. D., & Guimaraes, T. (1997). Successful strategies for user participation in systems development. *Journal of Management Information Systems, 14*(2), 133–150. https://doi.org/10.1080/07421222.1997.11518168

Michalewicz, Z., Schmidt, M., Michalewicz, M., & Chiriac, C. (2006). *Adaptive business intelligence*. Springer. https://doi.org/10.1007/978-3-540-32929-9

Mikalef, P., Pappas, I. O., Krogstie, J., & Giannakos, M. (2018). Big data analytics capabilities: A systematic literature review and research agenda. *Information Systems and E-Business Management, 16*(3), 547–578. https://doi.org/10.1007/s10257-017-0362-y

Naala, M., Nordin, N., Omar, W. A. B. W. (2017). Innovation capability and firm performance relationship: A study of PLS-structural equation modeling (PLS-SEM). *International Journal of Organization & Business Excellence, 2*(1), 39–50.

Ndler, D. A., & Tushman, M. L. (1980). A congruence model for organizational assessment. *Organizational Dynamics, 9*(2), 35–51. https://doi.org/10.1016/0090-2616(80)90039-X

Nandi, M. L., Nandi, S., Moya, H., & Kaynak, H. (2020). Blockchain technology-enabled supply chain systems and supply chain performance: A resource-based view. *Supply Chain Management, 25*(6), 841–862. https://doi.org/10.1108/SCM-12-2019-0444

Niú, Y., Ying, L., Yang, J., Bao, M., & Sivaparishan, C. B. (2021). Organizational business intelligence and decision making using big data analytics. *Information Processing and Management, 58*(6), 102725. https://doi.org/10.1016/j.ipm.2021.102725

Okkonen, J., Pirttimäki, V., Hannula, M., & Lonnqvist, A. (2002, May 9–11). Triangle of business intelligence, performance measurement and knowledge management. In *Proceedings of the 2nd Annual Conference on Innovative Research in Management, EURAM 2002*. Stockholm, Sweden.

Orlikowski, W. J. (1992). The duality of technology: Rethinking the concept of technology in organizations. *Organization Science, 3*(3), 429–447. https://doi.org/10.1287/orsc.3.3.398

Orlikowski, W. J. (2000). Using technology and constituting structures: A practice lens for studying technology in organizations. *Organization Science, 11*(4), 404–428. https://doi.org/10.1007/978-1-84628-901-9_10

Otoo, F. N. K. (2019). Human resource development (HRD) practices and banking industry effectiveness: The mediating role of employee competencies. *European Journal of Training and Development, 43*(3–4), 250–271. https://doi.org/10.1108/EJTD-07-2018-0068

Pandya, V. M. (2012, 6–7 September). Comparative analysis of development of SMEs in developed and developing countries. *International Conference on Business and Management*, (pp. 426–433). Phuket-Thailand.

Pee, L. G., & Kankanhalli, A. (2016). Interactions among factors influencing knowledge management in public-sector organizations: A resource-based view. *Government Information Quarterly, 33*(1), 188–199. https://doi.org/10.1016/j.giq.2015.06.002

Peng, D. X., & Lai, F. (2012). Using partial least squares in operations management research: A practical guideline and summary of past research. *Journal of Operations Management, 30*(6), 467–480. https://doi.org/10.1016/j.jom.2012.06.002

Petrimi, M., & Pozzebon, M. (2009). Managing sustainability with the support of business intelligence: Integrating socio-environmental indicators and organisational context. *Journal of Strategic Information Systems, 18*(4), 178–191. https://doi.org/10.1016/j.jsis.2009.06.001

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Popovič, A., Hackney, R., Coelho, P. S., & Jaklič, J. (2012). Towards business intelligence systems success: The roles of BI capabilities and firm performance relationship: A study of PLS-structural equation modeling (PLS-SEM). *International Journal of Organization & Business Excellence, 2*(1), 39–50.
Trieu, V. H. (2017). Getting value from Business Intelligence systems: A review and research agenda. Decision Support Systems, 93, 111–124. https://doi.org/10.1016/j.dss.2016.09.019

Tripathi, A., Bagga, T., & Aggarwal, R. K. (2020). Strategic impact of business intelligence: A review of literature. Prabhandhan: Indian Journal of Management, 13(3), 35–48. https://doi.org/10.17010/pijom/2020/v13i3/151175

Urbach, N., & Ahlemann, F. (2010). Structural equation modeling in information systems research using partial least squares. Journal of Information Technology Theory and Application (JITTA), 11(2), 5–40. https://aisel.aisnet.org/jitta/vol11/iss2/2

Venkatesh, V., & Morris, M. G. (2000). Why don’t men stop asking for directions? Gender, social influence and their role in society. MIS Quarterly, 24(1), 115–139. https://doi.org/10.2307/3250981

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3). https://doi.org/10.2307/30036540

Verona, G. (1999). A resource-based view of product development. The Academy of Management Review, 24(1), 132–142. https://doi.org/10.2307/259041

Vieae, S., & Van den Bunder, A. (2011). The secrets to managing business analytics projects. MIT Sloan Management Review, 53(1), 65–69.

Vidgen, R., Shaw, S., & Grant, D. B. (2017). Management challenges in creating value from business analytics. European Journal of Operational Research, 261(2), 626–639. https://doi.org/10.1016/j.ejor.2017.02.023

Wan, W. W. N., Luk, C. L., & Chow, C. W. C. (2005). Customers’ adoption of banking channels in Hong Kong. International Journal of Bank Marketing, 23(3), 255–272. https://doi.org/10.1108/02652320510591711

Wang, Y., & Byrd, T. A. (2019). Business analytics-enabled decision making effectiveness through knowledge absorptive capacity in health care. Journal of Knowledge Management, 23(3), 517–539. https://doi.org/10.1108/JKM-08-2015-0301

Wang, Y., Kung, L. A., & Byrd, T. A. (2018). Big data analytics: Understanding its capabilities and potential benefits for healthcare organizations. Technological Forecasting and Social Change, 126, 3–13. https://doi.org/10.1016/j.techfore.2015.12.019

Watson, W. E., Ponthieu, L. D., & Critelli, J. W. (1995). Team interpersonal process effectiveness in venture partnerships and its connection to perceived success. Journal of Business Venturing, 10(5), 393–411. https://doi.org/10.1016/0883-9026(95)00036-8

Wixom, B. H., & Watson, H. J. (2001). An empirical investigation of the factors affecting data warehousing success. MIS Quarterly, 25(1), 17–41. https://doi.org/10.2307/3250957

Wright, P. M., Dunford, B. B., & Snell, S. A. (2001). Human resources and the resource based view of the firm and the resource based view of the firm. Journal of Management, 27(6), 701–721. https://doi.org/10.1177/014920630102700607

Wright, P. M., McMahan, G. C., McCormick, B., & Sherman, W. S. (1998). Strategy, core competence, and HR involvement as determinants of HR effectiveness and refinery performance. Human Resource Management, 37(1), 17–29. https://doi.org/10.1002/(SICI)1097-0258(199821)37:1<17::AID-HRM3>3.0.CO;2-Y

Yeoh, W., & Popović, A. (2016) Extending the understanding of critical success factors for implementing business intelligence systems. Journal of the Association for Information Science and Technology, 67(1), 134–147. https://doi.org/10.1002/asi.23366

Zhang, K. Z. K., Cheung, C. M. K., & Lee, M. K. O. (2014). Examining the moderating effect of inconsistent reviews and its gender differences on consumers’ online shopping decision. International Journal of Information Management, 34(2), 89–98. https://doi.org/10.1016/j.ijinfomgt.2013.12.001