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

Malek AL-EDENAT*, Nayel ALHAWAMDEH

Department of Business Administration, College of Business, Tafila Technical University, Tafila, Jordan

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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; Arnott et al., 2017; Popovič 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).

*Corresponding author. E-mail: *mohaabmalek@yahoo.com*

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 (Popovič et al., 2012, 2014; Wang & Byrd, 2019).

Generally speaking, BI and BA are both of the furthermost broadly investigated notions and interests fields on both levels industrially, and managerially (Işik 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 (Bedeley 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 fr 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; Popovič 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 (Işik 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;

Popovič 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; Popovič 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-implemeComprehensivet 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 individemonstratingtinent, 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 syconductearly 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

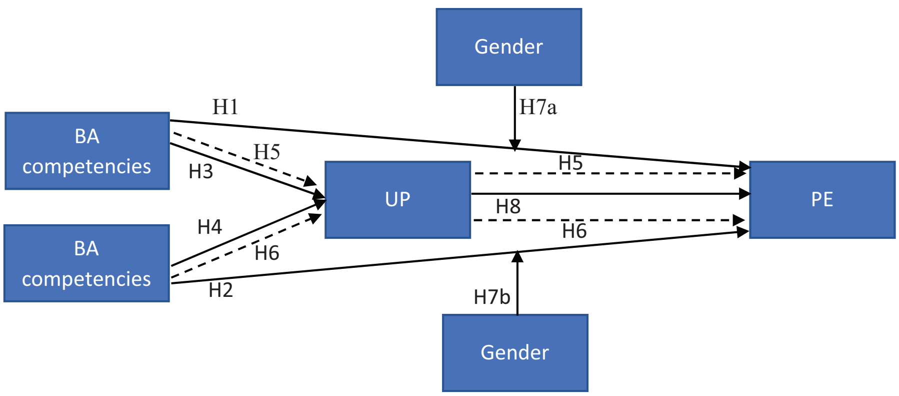

Figure 1. The hypothesizied relationships among the study's variables

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 penchants, 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:

H8: 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 (α = 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 (α = 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 (α = 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 (α = 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 confidentially 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

(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., 2012), 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; Schuberth, 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 1	0.823	0.000	0.90	0.91	0.8703
	BI 2	0.901	0.000			
	BI 3	0.874	0.000			
	BI 4	0.912	0.000			
	BI 5	0.917	0.000			
	BI 6	0.907	0.000			
	BI 7	0.889	0.000			
	BI 8	0.874	0.000			
	BI 9	0.821	0.000			
	BI 10	0.863	0.000			
	BI 11	0.886	0.000			
	BI 12	0.814	0.000			
	BI 13	0.897	0.000			

End of Table 2

Const-ruct	Code	Factor Loa-ding	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	0.87	0.86	0.7787
	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 3. Assessing DC (Correlations between Latent Variables and Square Roots of AVE)

	BI	BA	UP	PE
BI	0.933	0.488	0.684	0.396
BA		0.903	0.467	0.413
UP			0.860	0.387
PE				0.882

Apparently, as the data were collected for all variables with the same instrument, the potential for common method bias in the data is tested using both methods of Podsakoff et al. (2003). First, a common method constructs method to compare the estimated structural model path coefficients with and without the common method construct. The results showed no significant differences, suggesting that common method bias was not an issue in the data. Second, Harman's single-factor test was conducted, which showed the occurrence of distinctive factors in the un-rotated factor solution. Though these results do not exclude the probability of common method bias, however, it has been suggested that common method bias does not expect to explain the reported impacts (Andersson & Bateman, 1997).

2.3.2. Assessing the structural model

(R^2) is suggested for the model's predictive power (Sarstedt et al., 2014). Prior researches recommended and used threshold values of R^2 as 0.25, 0.50 and 0.75, indicating non-significant, moderate and significant relationships, respectively (Carranza et al., 2020; Hair et al., 2019; Tian et al., 2021). The results of the current study revealed that (0.412) 41.2%, (0.648) 64.8.4%, and (0.524) 52.4 variations in PE appeared because of the independent variables BI, BA and UP, respectively, as shown in Table 4. Then, the next step is to proceed toward examining the size of the effects (f^2) (Hair et al., 2019). It has been suggested that the values of 0.02, 0.15 and 0.35 reflect small, medium and great relevance, respectively. The results of the current study indicate that there is an effect, as shown in Table 4. Moreover, in their early work, Geisser (1974) and Stone (1974) recommended that the predictive relevance as an indicator of the model's out-of-sample predictive power and assessed using (Q^2). In that, the threshold of Q^2 values should be greater than zero for an explicit reflective endogenous latent variable, yet, it shows the path model's predictive relevance for a specific dependent variable (Hair et al., 2019). The results also indicate Q^2 values greater than zero as shown in Table 4. To deal with collinearity issues as well as common method bias, the current study uses the variance inflation factor (VIF). In which values should be less than 3.3 (Hair et al., 2011). Further, Standard root means square residual (SRMR) is used to examine the root mean square discrepancy between the observed correlations and the model-implied correlations, which also assesses the absolute measure of fit. However, Hu and Bentler (1998) recommended that an SRMR value of less than 0.08 is considered an acceptable fit. The results of this study show a good model fit as represented in Table 4.

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		2.781	

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 BI, 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; Işik 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 shown 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 functionalities to encourage the knowledge practices of numerous sorts of decision-makers (Lahrmann et al., 2011; Işik et al., 2012; Sangari & Razmi, 2015; Santiago Rivera & Shanks, 2015; Yeoh & Popovič, 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 (Savlovschi & Robu, 2011); however, different types of organizations to be studied may exhibit different results.

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