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Understanding self-directed learning behavior towards digital competence among business research students: SEM-neural analysis

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Abstract

Digital competence among business research students is heralded as a pragmatic expression of the quality of research output and effective collaboration. Self-Directed Learning (SDL) is a resourceful personal and professional development technique, yet there is minimal research on SDL for digital competence among business scholars. This study investigates the behavioral aspects of business research students to engage in the SDL mechanism for digital competence. A hypothesis-based research framework was outlined through Perceived Usefulness (PU), Facilitating Conditions (FC), Self-Directed Learning Readiness (SDLR), Personal Innovativeness (PI), Computer Self-Efficacy (CSE), and Behavioral Intention (BI). Data were collected through a quantitative survey and then analyzed by the novel multi-analytical approach, i.e., Partial Least Squares Structural Equation Modelling (PLS-SEM) to test hypotheses, Artificial Neural Network (ANN) to manage the non-linear associations in the model and to rank the predictors, and Importance Performance Map Analysis (IPMA) to assess the variables through importance and performance chart. Data analysis showed that all variables were significant predictors of SDL behavior where PI and CSE were prominent model antecedents. The study's contributions towards knowledge included the practical implications for boosting digital competence among young researchers, providing the in-depth analysis of antecedents of SDL behavior, and validation of multi-analytical tools in technology integration literature.

Keywords ANN · Digital competence · IPMA · PLS-SEM · Self-directed learning

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1 Introduction

Industrial revolutions initiated the invention of artefacts for human wellbeing through electronic equipment, telecommunication devices, and mobility units. Such machines are becoming more innovative with modern technology as man has programmed and trained these artefacts to perform activities through artificial intelligence, i.e., deep machine learning methods. For instance, self-driving cars operate through machine learning, by which cars can self-learn and operate intelligently with the time and experience of their functions. With such a pace of technological integration, humans also need to be trained and skilled in innovative digital tools and techniques to become digitally competent. Being literate in modern technology usage is characterized as digital literacy. Using specific digital tools like operating the computer program, communicating through the internet, and lettering the words, numbers, and codes do not correspond to the principles of digital competence. The ability to interact, communicate and reap the benefits from technology in the respective profession is termed digital competence (Spante et al., 2018). Digital competence being an advanced shape of digital literacy is based on a learning trilogy, namely, the competency that refers to obtaining knowledge of the digital skillset, the usability, i.e., applying such skills in the destined field, and transformative capability such as making use of creative and innovative outcomes (Marsh, 2018). Digitally competent individuals are proven more efficient and convenient in professional duties (Geng et al., 2019). Digital competence levels and types vary according to the professions and circumstances. For example, a graphic designer necessitates more diverse digital skills than a sales manager, and an academician requires a different digital competency level than an accountant.

To become digitally competent towards task accomplishment, an individual (i.e., student, employee, or citizen) impulsively involves self-directed use of learning possibilities, however, attributable to infrequent prospects with economic and geographical circumstances, everyone cannot be proficient in updated technological methods for personal and professional purposes. In such scenarios, self-education and development, being the unique approach to learning (Sumuer, 2018), can support as an enabler of digital competency. Students self-directed learning (SDL) process to upskill their knowledge level is a regular practice (Sumuer, 2018).

Business study segments are considered non-technical areas where technology use applications have minimal role compared to computer science and engineering fields. The conceptions of advanced mathematical and statistical analysis and data programming software were not stapled in business studies. Business research students currently engage in various digital tools and techniques to conduct research activities. As the induction of digital tools and techniques has shaped how business research mechanisms are being steered, research students also currently comply with digital competency and professional capabilities. Searching data, sorting information, lettering the texts, codes, and numbers, illustrating the graphs, vectors, and charts, authoring manuscript, analyzing complex statistical and mathematical calculations, managing the data, presenting the paper, publishing the research work, and establishing the digital identity encapsulate the implications of digital competency. A better understanding of necessary skills in this regard helps to conclude fruitful inferences in research matters. The significance of digital competence in business studies directs the excellence in research work and academic performance. Being digitally competent paves the way toward quality publications, practical learning, and a collaborative network.

As learning trends have been shaped due to the integration of digital works, the self-initiated learning process still needs to explore the attributes and effective elements for purposeful outcomes (Alvermann & Sanders, 2019). The decision to engage in the SDL process is solely an individual's discretion of being influenced by the circumstances, knowledge level, and perception about learning goals (Boyer et al., 2014). An SDL mindset in students emerges through positive and inspiring surroundings and sufficient time-span to vigorously participate in knowledge enhancement activities (Fok et al., 2018). Given the vitality of upskilling digital tools for research purposes, it is imperative to investigate the facts that drive SDL behavior towards digital competence. By keeping in view such impressions, this study attempts to answer the following research questions:

- Do business research students engage in self-directed learning toward attaining digital competence?
- Do business research students comply with various behavioral and perceptive aspects and procedures in self-directed learning towards digital competence?
- What are the vital impacting elements on SDL behavior towards attaining digital competence?

Understanding the essence of business scholars' self-initiated learning towards digital competence is the impact matter of this research. Studies in this domain are limited and insufficient in explaining SDL behavior's detailed circumstantial and perceptive pattern. The available studies enlisted the SDL behavioral intention towards acceptance of learning modes among students (Fok et al., 2018; Mahmoud et al., 2016), assessing personality traits (Lin et al., 2016), investigating social influence, capacity and affection support (Mahmoud et al., 2016), gauging mobile SDL (Eroğlu et al., 2017), understanding learners' perception in behavioral shaping (Alotaibi, 2016) and establishing the SDL readiness scale (Zhoc & Chen, 2016). The SDL behavior valuation was also primarily conducted for language learning students (Fok et al., 2018; Lai, 2013), nursing graduates (Cadorin et al., 2015), and university students for m-learning (Eroğlu et al., 2017; Gokcearslan, 2017). The digital competence among business students was assessed for general computer use activities like knowledge of ICT hardware and applications (Florjančič & Wiechetek, 2019). Another study described the role of digital competence in the students' informal learning behavior through digital tools. The digital learning behavior was assessed through generalized digital competence parameters with personal innovativeness and attitude (He & Zhu, 2017), however, such studies had not discussed the digital competence of research students nor contemplated the SDL behavior for digital competence, though impacting factors of SDL behavior were broadly debated.

While debating the determining factors, it is evident that SDL behavior is predominantly centred on the individual inclination towards technology and digital systems. Personal innovativeness drives digital literacy among students (Nelson et al., 2011). While numerous kinds of research portray that personal innovativeness strengthens the behavior toward blended (Geng et al., 2019) and self-directed learning (Karimi, 2016). Digital competence is accepting the technology and reaping benefit for meaningful purposes. In this regard, the perceived significance and usefulness of the SDL process towards digital competence can be impactful as perceived usefulness has a positive effect on behavior for SDL among students (M. K. Hsu et al., 2009). It also influences behavior toward digital skills learning (Amornkitpinyo & Piriyasurawong, 2015). The learning process among students also correlated with circumstances and facilitating conditions such as compulsory physical and digital resources, supporting environment, and informal guidance (Sedek et al., 2015). A readiness scale to measure the SDL, i.e., SDLR, was established to understand the student's behavior towards the learning mechanism (Lin et al., 2016). Previous research also indicated that proficiency in computer knowledge, i.e., computer self-efficacy, helps to engage in the learning process (Chen, 2013). Besides, few studies highlighted the relationship between self-directed learning and digital competence. They presented the basic level concepts such as digital competence parameters for informal learning (He & Zhu, 2017), particulars of business students' digital competence in general form (Florjančič & Wiechetek, 2019) and readiness scale for SDL process (Lin et al., 2016), however, cognitive, and situational aspects of SDL behavior for digital competence were not examined or interpreted in previous studies. This literature gap signifies the rationale for this research work. Likewise, the digital skill development for business research students was also not debated in the literature. By conducting such study, it could instigate better insight of digital competence among business research students and contribute to knowledge and practice in today's tech-enabled era.

Another significant issue was also orchestrated in preceding literature on SDL behavior that research studies primarily incorporated the conventional statistical methodologies, i.e., linear regression and Structural Equation Modeling (SEM) analysis (Boyer et al., 2014; Lai, 2013; Lin et al., 2016; Mahmoud et al., 2016; Prior et al., 2016). While through SEM, it is not feasible to investigate linear and non-linear relationships among the model variables; moreover, contemplating the role of all predictive variables is also not attainable through deducing the linear relationship (Leong et al., 2020a). This limitation of SEM analysis can be mitigated by adding two-stage SEM and Artificial Neural Networks (ANN) analysis. Due to this machine learning technique, ANN determines the accurate predictive power compared to SEM; though, ANN cannot carry out the hypothesis testing and confirmation. Consequently, a two-stage analysis is practised by which SEM performs hypothesis testing and then ANN is applied through a feed-forward backward propagation algorithm (Leong et al., 2020a, b.

Moreover, Importance Performance Map Analysis (IPMA) analysis is considered a valuable tool for indicating practical implications on a performance and importance basis, which helps the authorities to heed more individual factors (Leong et al., 2020a). Literature on SDL and digital competence did not consider IPMA to propose the vital predictor in previous studies. Therefore, this study has incorporated the SEM-ANN approach to confer the research results more standardized with higher prediction accuracy and IPMA for a better understanding of the modelled variables from a policy implementation view.

The leading urge for a techno-literate mindset and its prominence in the business research process compels the investigation of self-directed learning behavior and its antecedents. The prime motivation for this study is the need to propose a research framework that deals with previous studies' shortcomings in predicting business scholars' SDL behavior towards digital competence. The deficient manifestation of vital predictors of SDL behavior towards digital competence and the absence of advanced statistical and machine learning approach to infer the resourceful research analysis are noticeable in the previous literature. The study aims to elucidate the understanding of SDL behavior in business research students and investigate their behavioral elements towards digital competence. The theoretical research broadens the scope of SDL behavioral intention to incorporate perceptive factors towards the digital competence goal. The research work may benefit the stakeholders in academia towards research process integration by understanding the association between SDL behavior and digital competence. Towards comprehending the SDL behavior mechanism, a research framework was developed from theoretical concepts and psychological elements such as perceived usefulness (PU), computer self-efficacy (CSE), personal innovativeness (PI), facilitating conditions (FC), self-directed learning readiness (SDLR) and behavioral intention to engage in SDL process (BI) towards digital competence. The framework was employed through hypotheses explaining how the numerous factors interrelate with each other to affect students' SDL behavior towards digital competence. A causal research survey was conducted to validate the research framework from business research students. Then SEM-Neural analyses were performed to conclude the inferences for theoretical and practical implications.

The structure of the paper is organized as follows: Section 2 (literature review) explains the role of SDL, digital competence, theoretical perspective, and hypothesis development. In Section 3, methodology design, data collection and data analysis tools for the study are described and discussed. Section 4 presents the data analysis results based on demographics details, common method bias, SEM, IPMA and ANN models. Finally, Section 5 presents the detailed discussions and findings of research inferences, along with the study contributions, limitations, and future recommendations.

2 Related work

2.1 Self-directed learning (SDL)

In today's world, the advent of digital self-learning is the heightened consequence of technological understanding and its penetration at the individual level. SDL concept can better fortify the elaborative pattern of personal learning strategies toward knowledge innovation. In the SDL approach, the individual initiates the learning process without the mentor's conventional assistance. The process of SDL comprises systematic steps such as diagnosing the learning needs, postulating the goals and objectives, identifying the necessary resources (i.e., human and material) for learning, then choosing and implementing the appropriate plan of actions and strategies, and finally evaluating the learning outcomes. For better understanding, SDL is categorized into four types, i.e., persuaded, synergistic, voluntary, and scanning, based on the significance and situational context (Boyer et al., 2014). Persuaded SDL explores the support of authorities towards learners' needs on a mandatory basis, and organizations control the learning process. The synergistic SDL accords with a gateway opportunity where the individual chooses from organizational-provided learning facilities, and the learner assesses the learning process. The voluntary SDL deals with the self-realization of learning need to excel in the job by individuals and independently look for the opportunities and resources for learning goals. The fourth form of SDL slightly differs from voluntary SDL as it seeks continuous learning and development process for a cause that does not have a determined endpoint is known as scanning SDL. It includes highly volatile subject fields, for instance, the stock market, health technology, electronics, information system, artificial intelligence, gaming, transportation, and computer programming. Using the SDL approach hails the students' and employees' creativity and craving for learning (Boyer et al., 2014; Lai, 2013). Even though the trends of e-learning and m-learning are confined to the specific course and subject matter, rapid digital integration calls for the realization of digital competence at the individual level (Choi et al., 2014; Eroğlu et al., 2017; Gokcearslan, 2017; Lounsbury et al., 2009).

2.2 Digital competence for business research

Digital competence is a compilation of skills, knowledge and attitudes that facilitate the confident, creative, and critical use of technologies and systems (Pettersson, 2018). The talent empowers an individual to become a staunch digital citizen, to make interactions and collaboration digitally, to complete a job or tasks digitally, and to be proficient in managing data and computational expertise. For decades, the research work was associated with spending time with books and literature in libraries and discussing with professors and fellow researchers. However, digital integration in education and research has shaped the mechanism, and individual researchers need to learn various computer programs and digital expertise to comply with multiple research processes. In current digital integration, conducting effective research in business studies entails diverse technological learning and expertise. Considering the European Digital Competence Framework (European Commission, 2019) and practical perspectives of the research process, the digital competence for business students to conduct academic research entails the five elements, as illustrated in Fig. 1, i.e., 1) information gathering, 2) content creation, 3) data analysis, 4) publishing research, and 5) digital identity. Data gathering competence entails assembling and organizing the research literature and data from verified and accurate digital libraries through keywords and filters. Content creation explains the process of lettering the data (with word processors or keying in through command-line programs

Fig. 1 Digital competence framework in research

like LaTeX), binding with the composing procedure (through proofreader programs), and citing the literature (through reference manager tools), moreover, illustrating and visualizing the research work (by vectors, images, graphs, flowcharts, and slides through different multimedia designer packages). Data analysis comprises analyzing the research data with the help of statistical and mathematical software such as SPSS Statistics, SPSS AMOS Graphics, SmartPLS, Mplus, Lisrel, R, Stata, SAS, Vensim, RapidMiner, and Python, depending on the requirements of analysis. Data publishing involves disseminating the research work through the internet by understanding the pertinent prerequisites such as journal information, indexing and metrics, and online submission system, along with comprehending the typesetting techniques for publishing and printing purposes. Digital identity calls for collaborating the learning activities by connecting the academic networks and research plateforms. It induces the utility patterns of various academic profiles and educational, social networking.

2.3 Theoretical perspective

Numerous theories explain the behavior modelling process, predominantly towards technology use. Theory of Planned Behavior (TPB) is considered a central behavioral assessment technique that demonstrates that any behavior to perform the action is backed by three significant predictors, i.e., attitude, perceived behavior control, and subjective norm. The attitude is influenced by social pressure, personal belief, or confidence of action to indulge in a particular activity. TPB has been proved an effective behavior assessment tool in learning scenarios. Towards self-directed use of the digital tool in language learning, TPB acclaimed its recognition by predicting the behavior and its predictors among students (Lai, 2013). TPB also explained the behavioral pattern of students learning through various types of technologies in a self-directed context (Gokcearslan, 2017), however, TPB does not engage with the relativity of technology nature, such as expected usability outcome or easiness. Besides this, Technology Acceptance Model (TAM) aims to cater behavior modelling by positive usability returns of technology with reduced usableness exertion (Davis, 1989). TAM is considered one of the most validated information system theories to understand human behavior in the tech era. TAM has two main elements, perceived usefulness (PU) and perceived ease of use (PEOU), to shape the positive or negative attitude (ATT) that leads to behavioral intention (BI) of acceptance or reluctance towards performing particular behavior and action. SDL through new technology devices is validated by TAM (Gokcearslan, 2017). As technological innovations emerge, the nature and level of digitalization also vary.

Similarly, the parameters of human interaction with technology also update. The TPB and TAM had certain limitations in predicting the behavior as the nature of technology, circumstances, regulations, individual's mindset, and learning culture has been altered. The extended version of the TAM model was implied as the Unified Theory of Acceptance and Use of Technology (UTAUT). This model modernized the concepts of TAM, i.e., perceived usefulness to performance expectancy and perceived ease of use to effort expectancy. Besides, UTAUT had also added social influence and facilitating conditions to assess the behavior towards technology-related behavior. UTAUT has been vibrant among learning modes such as e-learning, m-learning, and ubiquitous learning. To evaluate the digital competence impact on personal performance, the UTAUT fixated on the behavioral assessment (Marsh, 2018).

This study's SDL behavior is framed through the above-mentioned information system theories with self-directed learning phenomena. The predefined behavioral models are limited to explaining the one-dimensional aspect of behavior while adding circumstantial variables such as SDL readiness, personal innovativeness, and computer self-efficacy would support in better understanding of the behavioral assessment. TPB and TAM have an impact analogy of predecessors of behavior. PU from TAM is considered for explaining the significance of SDL behavior among business students towards digital competence. Computer Self-efficacy that leans on the knowledgeable affirmation of IT and Personal Innovativeness that deals with a strong inclination towards the digital world could predict the SDL behavior.

2.4 Hypothesis development

2.4.1 Perceived usefulness

Perceived Usefulness (PU) is a cognitive expression relating to the perception of performance advantages. PU is a vital factor in the TAM model that relates to perceiving positive outcomes before embarking on specific behavior related to technology use. In today's society of personal learning and development, the practicality of SDL has emerged among learners, and their perception of online education has become positively correlated with learning gains. The importance of digital skills in school is accredited, and many measures have been taken across the globe to boost it (Fok et al., 2018). Likewise, in other society innards, students' behavior also perceives the ultimate benefits at the initial stage to engage in the learning process. For instance, behavior towards statistical software usage is influenced by the perceived importance of the tool among MBA students in a USA university (M. K. Hsu et al., 2009). Improving the digital competence among students, the perspective of usefulness is an essential element of behavioral intention (Gie & Fenn, 2019). For the 21st-century skills set among undergraduate students in Malaysia, PU played a crucial role in understanding digital competence behavior (Amornkitpinyo & Piriyasurawong, 2015). Similarly, a study in Turkey portrayed that SDL behavior among students had a positive relationship with the usefulness of digital tools. PU was found to be highly correlated with SDL behavior (Gokcearslan, 2017). By keeping the literature analogy, this study also proposes that PU can positively influence the business research student's behavioral intention towards SDL for digital competence. Hence it is hypothesized that:

H1: *Perceived Usefulness (PU) will significantly impact the Behavioral Intention (BI) to engage in SDL for digital competence.*

2.4.2 Facilitating conditions

UTAUT reiterates the multiple aspects of behavioral dynamics in digital vogue. As positive and negative circumstances exist in adopting digital tools, the enablers and barriers of particular behavioral use are termed Facilitating Conditions (FC) (Venkatesh et al., 2012). In the SDL scenario, the FC is the technical and manual support in achieving the learning outcome. For instance, the utility guide of a specific computer program or technical function, expert panel advice in completing the task, and guidance from seniors towards solving the issues. Digital competence involves understanding various information and communication technologies functions while support from vendors, independent users, and focus groups are facilitating conditions in this scenario. In Ubiquitous technologies, the subject matter of digital competence phenomena, FC has a positive impact on behavioral use in learning (Sedek et al., 2015). In a UK-based study, the technical competence in the digital workplace evolved from numerous predecessors that support the individual's learning behavior (Marsh, 2018). Another survey of self-directed learners from Hong Kong echoed the prominent role of learning motivation and facilitating conditions in students' behavior (Lai, 2013). In this context, the FC is proposed to predict the SDL behavior of business research students towards digital competence. Hence it is hypothesized that:

H2: *Facilitating Conditions (FC) will significantly impact the Behavioral Intention (BI) to engage in SDL for digital competence.*

2.4.3 Self-directed learning readiness

Learning readiness encapsulates a positive approach, strong personal belief, and self-management (Fisher & King, 2010). The desire to learn directed through self-control and intentional learning (Demir & Yurdugül, 2013) coincide with the willingness concept of SDL. Individuals' eagerness for SDL correlated with social, psychological, and incidental components. SDL readiness differs from self-regulated learning readiness as SDL readiness deals with adult education while the latter mainly focuses on younger students. SDL effectively predicts learning behavior in blending learning (Geng et al., 2019). Mobile learning readiness behavior is backed by a robust optimistic learning methodology, self-efficacy, and a self-directed learning approach. Students with a high degree of SDL readiness are tempted to be autonomous learners (Lin et al., 2016). Digital competence among business research students can be highly predictable with such a level of autonomy in learning behavior. SDL readiness is a personal trait and forerunner toward generalized beliefs about technology and innovation in learning (Zhoc & Chen, 2016). SDL readiness in research learning behavior towards digital competence ropes the business students to command their research learning progress, take control of study plan, time management, and self-disciplining. In this context, the author proposes that SDL readiness will influence the behavioral intention to take the initiative of SDL in business research students to excel the digital knowledge and expertise. Therefore, it is hypothesized that:

> ***H3:*** *Self-Directed Learning Readiness (SDLR) will significantly impact the Behavioral Intention (BI) to engage in SDL for digital competence.*

2.4.4 Personal innovativeness

The psychological pinpoint of learning behavior stems from the individual's personality. The open-mindedness toward innovations and contemporary techniques is the emergence of pioneers in the learning systems, and this progression is named personal innovativeness (PI). The gradual and rapid transformation of life segments in modern-day endeavors requires innovativeness to give the advantage in fulfilling daily activities, professional duties, and learning pursuits. PI was determined to understand the individual's personality toward Information Technology (Agarwal & Prasad, 1998). PI shares the nodes of willingness to embrace innovation. PI impacts the behavioral intention to engage the learning behavior. In digital knowledge acquisition, PI strongly predicts technology tool and process usability. As in a Malaysian university, personal innovativeness significantly impacted the usefulness of mobile learning behavior (Joo et al., 2014). Students' behavior toward digital competence and PI appeared strongly interconnected and correlated (Nelson et al., 2011). An Australian-based study portrayed that learning behavior in blending learning also strengthens PI's role in behavior modelling (Geng et al., 2019). Based on TAM theory (Joo et al., 2014), personal innovativeness was assessed for learning behavior among 350 university students. PI was a positive indicator of the perceived usefulness of the learning behavior. The behavioral intention of learning students is indirectly impacted by personal innovativeness. PI formulated the major scales to understand the readiness level in SDL behavior to understand digital learning (Geng et al., 2019). In another study on SDL adoption behavior in the UK, PI emerged as the strong prognosticator of SDL behavior among university students. Moreover, PI showed significance in both formal and informal learning behavior (Karimi, 2016). In this scenario, the author proposes that the implication of personal innovativeness on SDL behavior towards digital competence will be vibrant and compelling. Therefore, it is hypothesized that:

H4: *Personal Innovativeness (PI) will significantly impact the Behavioral Intention (BI) to engage in SDL for digital competence.*

2.4.5 Computer self-efficacy

Efficacy is the self-believing approach in challenging situations in life. Believing in self-attributes towards the novel diaspora enables confidence and optimistic stimulus. Computer Self-Efficacy (CSE) is an updated expression of self-efficacy to bridge the gap between the digital environment and personal technical skills to engage in the process. CSE is an individual's competence to apply computer-related skills in IT-relevant functions (Compeau & Higgins, 1995). Indeed, by engaging in non-traditional procedures like SDL behavior toward digital competence, individuals rely on their potential and aptitudes in the technological aspect. To comprehend this role of CSE, research in the USA discovered that BI of management studies graduates towards IT entrepreneurial activities was mainly predicted by CSE (Chen, 2013). In other empirical findings of statistical functions behavior, MBA students' BI was assessed by computer software self-efficacy in statistics through PU and PEOU (M. K. Hsu et al., 2009). Furthermore, in Taiwan, the role of CSE towards BI in electronic book publishing was supported through TAM theory and explored the prediction value among university students (Liao et al., 2018). Towards Web 2.0 technologies for study purposes, Taiwanese research concluded that CSE was the leading influencer on college students' BI towards SDL with technology. By keeping such inferences, the study proposes a positive relationship between CSE and BI of business research students to be involved in SDL behavior towards digital competence. Therefore, it is hypothesized that:

H5: *Computer Self-Efficacy (CSE) will significantly impact the Behavioral Intention (BI) to engage in SDL for digital competence.*

2.5 Research framework

By comprehending the factors from IS theories in the SDL context, a research framework was postulated as sketched in Fig. 2. The proposed model hypothesized the relationship among the model factors, i.e., PU, SDL Readiness, FC, PI, and CSE, towards BI of business research students to engage in the SDL behavior. These relationships were tested through (PLS-SEM) via surveyed data to validate

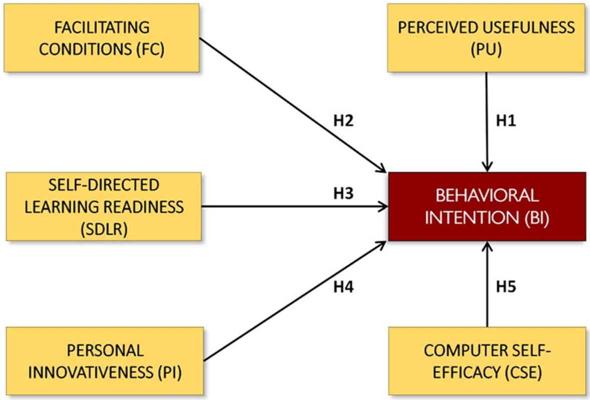


Fig. 2 Research framework

the hypotheses describing the predictors' impact on SDL behavior for gaining digital competence.

3 Methodology

This study commenced the methodological patterns of Saunders' Research Onion (Saunders et al., 2015) and adopted the validated behavioral modelling studies (Leong et al., 2020a, b to conduct the research process. The positivist research philosophy was designated as causal relationships being determined through quantitative analysis (i.e., statistical inferences). The research approach involved the theoretical aspects of the study as deductive to comprehend the already validated theories and concepts. Methodology for the analysis comprised the mono method as merely a quantitative scheme through a cross-sectional survey was used to collect the data.

A structured questionnaire was designed to gather data from research students through the internet. The questionnaire was based on two sections: respondents' demographic information was listed in Section 1, while questions about causal variables in SDL behavior were part of Section 2. The questions items of survey variables were adapted from previously validated studies with a total of 30 items of 6 variables, i.e., 05 items for perceived usefulness (Davis et al., 1989), 05 items for SDL readiness (Lin et al., 2016), 06 items of personal innovativeness (Agarwal & Prasad, 1998), 05 items of facilitating conditions (Venkatesh et al., 2012), 04 items of computer self-efficacy (Compeau & Higgins, 1995) and 04 items of behavioral intention (Ajzen, 1991). The 5-point Likert scale, where 1 = "Strongly Disagree" to 5 = "Strongly Agree", was used to measure the responses. Experts assessed the questionnaire before distribution to ensure the language, subject matter and understanding of measured items for respondents.

The data was collected through a close-ended structured questionnaire using a convenience sampling method from social media platforms. The online form was shared in numerous research community groups on Facebook. Such groups aim to provide higher education institutions' students with the platform to collaborate and develop a mutual guidance network (Thai et al., 2019). University students use such groups for learning motivations (Ahern et al., 2016) and preferring Facebook as a tool for data collection as a more valuable and accurate way to reach the targeted audience (Cunha et al., 2016; Rife et al., 2016; Whitaker et al., 2017). The researchers maintained informed consent in written form to familiarize the participants with the research purpose, the researcher's responsibility toward the collected data, participants' privacy rights, the outlook of future benefit from using their opinions in the research, and the disposal of data. Data were collected between June 2020 to September-2020. The research respondents were business research students of Master's and PhD levels, and a total of 214 responses were recorded, which is appropriate sample size for SEM analysis (Hair. et al., 2014).

Partial Least Square Structural Equation Modeling (PLS-SEM) and Artificial Neural Network (ANN) were implied in two stages to analyze the collected sample. PLS-SEM is a prominent analysis tool in business, information systems, and education studies (Amaro et al. 2015); Charmchian Langerodi & Dinpanah, 2017; Sepasgozar et al., 2018; Verma et al. (2018); Teo et al., 2017). PLS-SEM also dominates the CB-SEM technique by explaining the accurate variance of indicators of the studied model (Hair et al., 2012). For this study, PLS-SEM analysis encapsulated numerous techniques to make data refined, valid, and reliable for valuable inferences. As convenience sampling in quantitative studies can raise issues regarding the subjective nature of selecting the respondents and data bias, the common method bias (CMB) test was also conducted to handle such issues (Alshurideh et al., 2020; Podsakoff et al., 2003). In the next stage, the author verified the reliability and validity of the data, and then factor loadings of questionnaire items were assessed. Finally, the path analysis of model variables was discussed to conclude the hypotheses' results. Subsequently, the ANN model was calculated. As PLS-SEM cannot calculate non-linear relationships in the model, the ANN model, being the machine learning technique, can well-predict such relationships more accurately (Henseler et al., 2009). In such scenarios, PLS-SEM and ANN are vital to one other in the two-stage analysis (Leong et al., 2020b). Variables filtered as significance towards dependent variable through hypothesis testing were assessed in the ANN model where root mean square error (RMSE) values and normalised importance had resulted. Furthermore, author have added the importance-performance map analysis (IPMA) to understand the important variables in the models which could support the factors' performance assessment (Gbadebo Salimon & Hassan Gorondutse, 2018; Otto-von-guericke-universit et al., 2017).

4 Results

4.1 Demographic results

The questionnaire data was collected through online forums from business research students, and convenience sampling was applied. The demographic variables included gender, age, education level, location, and institute type.

According to collected data, male with 72%, the age group (26–30) with 37%, private university with 63%, and doctoral-level education with 61% dominated the demographic components. Furthermore, respondents belonged to numerous territories from southeast Asia to south Asia, with higher responses from Malaysia (113) and Indonesia (32). Moreover, 17 (8%) responses were cumulatively received from various locations such as Thailand (4), Philippines (3), Saudi Arabia (3), Iran (2), Egypt (2), Sri Lanka (1), Germany (1), and Turkey (1). The details of the demographic are presented in Table 1.

4.2 Common method bias (CMB)

These two approaches were used to test the CMB. First, to ensure that the gathered data do not come up with CMB issues, Harman's single-factor was conducted with six factors (perceived usefulness, facilitating conditions, personal innovativeness, computer self-efficacy, self-directed learning readiness, and behavioral intention) (Jarvis et al., 2003). These six factors were then loaded into a single factor. The resulting assessment depicts that the highest variance explained by the newly generated factor was 25.92%, which is beneath the threshold value of 50% (Podsakoff et al., 2003). Thus, there were no issues concerning the CMB in the assembled data. The second approach was observed, which utilizes a full collinearity test to assess CMB in PLS-SEM (Kock & Lynn, 2012). The method determines the variance inflation factor (VIF) for all independent variables in the proposed model. VIF values of all factors were less than 4, which is lower than the acceptable threshold (Hair et al., 2010).

4.3 Measurement model

The basics of SEM analysis ensure that data are reliable and valid upon the given standards. Data are collected through variable items. Scores of these items are assessed for reliability, impartiality, tractability, and authenticity before SEM. Reliability analysis comes first in this procedure, where it guarantees the internal consistency of items as a group. The given standard of reliability is Cronbach Alpha

Table 1 Demographic results

Gender	%	Institute	%
Male	72	Public	37
Female	28	Private	63
Age Group	%	Country	%
20–25	32	Malaysia	53
26–30	37	Indonesia	15
31–40	24	Pakistan	12
40 Above	07	India	07
Study Level	%	Bangladesh	05
		Misc	08
Masters	39		
PhD	61		

Table 2 Reliability and validity results

Variable	Items	Cronbach's Alpha	CR	AVE
BI	4	0.84	0.893	0.676
CSE	4	0.803	0.871	0.629
FC	5	0.786	0.852	0.536
PI	6	0.891	0.917	0.648
PU	5	0.849	0.898	0.689
SDLR	6	0.856	0.889	0.573

Table 3 HTMT ratio of correlation

	BI	CSE	FC	PI	PU	SDLR
BI						
CSE	0.634					
FC	0.396	0.252				
PI	0.663	0.619	0.377			
PU	0.403	0.208	0.207	0.285		
SDLR	0.291	0.161	0.084	0.234	0.181	

level > 0.70. In this survey, each factor's items represented the valid reliability level from 0.786 to 0.891, as presented in Table 2. To measure the convergent validity of data for SEM feature engages composite reliability, which deals with the consistency of items value. The acceptable threshold for composite reliability is more than 0.70. Here this internal consistency value of all variable items ranged from 0.871 to 0.917, as depicted in Table 2, which proved the valid consistency level in the data. Another tool to portray convergent validity is Average Variance Extracted (AVE). AVE is the average variance of items that a variable describes. The threshold value of AVE should be greater than 0.50, while surveyed data explained that the AVE values of all constructs are more than benchmarked value.

4.4 Discriminant validity

Another measure of the validity of data for causal analysis is discriminant validity, which ensures no correlation between constructs at such a higher level that makes these identical. The Hetrotrait-Monotrait ratio of correlation (HTMT) method was used to examine discriminant validity, where the threshold value of each relationship correlation is limited to 0.90 (Hair et al., 2012). As per the results, all constructs validate the minimum value of HTMT, as explored in Table 3.

4.5 Factor loadings

These are the correlation coefficients between items and the variables directly observed through the questionnaires, termed factor loadings. Factor loadings in factor analysis are meant to assess whether items of a factor are coherent and stable according to the researchers' interpretation of the nature of that variable (Hair et al., 2012). These loadings values are required to reach 0.5 when the reliability exceeds 0.7 (Truong & McColl, 2011). In this study, outer loadings ranged between 0.57 to 0.82. as described in Table 4, overall reliability > 0.7, AVE > 0.5, and CR > 0.7 to make the factors acceptable.

4.6 Path analysis

Following data reliability, validity, and factor analysis, the author conducted the path analysis in SmartPLS 3.3. Path analysis depicts the causal relationship between the dependent variable and independent factors, as shown in Fig. 3

Table 4 Factor Loadings

Factor	Items	Loadings
PU	PU1	0.711
	PU2	0.855
	PU3	0.791
	PU4	0.804
	PU5	0.804
CSE	CSE1	0.820
	CSE2	0.816
	CSE3	0.824
	CSE4	0.704
SDLR	SDLR1	0.764
	SDLR2	0.771
	SDLR3	0.704
	SDLR4	0.671
	SDLR5	0.792
	SDLR6	0.829
FC	FC1	0.650
	FC2	0.767
	FC3	0.762
	FC4	0.793
	FC5	0.678
BI	BI1	0.779
	BI2	0.836
	BI3	0.818
	BI4	0.854
PI	PI1	0.814
	PI2	0.788
	PI3	0.806
	PI4	0.836
	PI5	0.810
	PI6	0.773

Fig. 3 Measurement Model

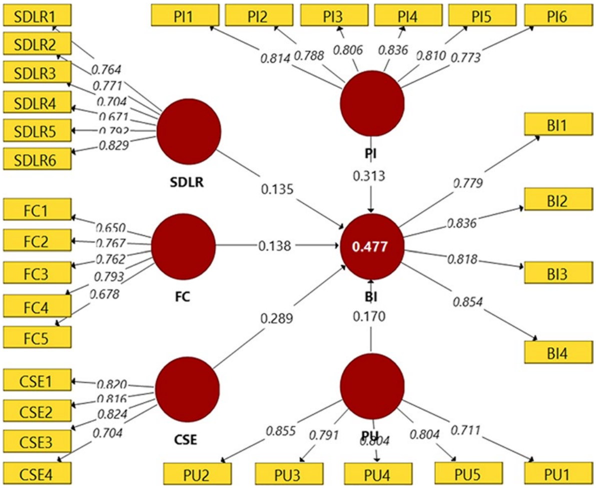
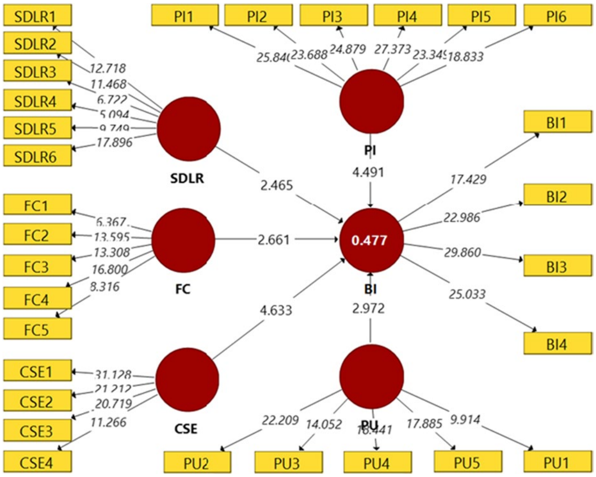


Fig. 4 Structural Model



(measurement model) and Fig. 4 (structural model). As per the measurement model, the total change in BI due to model predictors resulted in $R^2 = 0.477$ (i.e., 47.7%). It shows that the hypothesized variables can impact behavioral intention at a good pace. The path coefficient of variables that describes the predictors' impact on BI are also demonstrated in Fig. 3, where PI leads with a value of 0.313. In hypothesis testing, the set criteria to qualify for hypothesis acceptance, the result should meet the minimum value of the critical ratio (i.e., $CR > 1.96$) and significance level (i.e., the p-value) less than 0.05. As resulted in Table 5 and Fig. 4, all proposed hypotheses in the structural model indicated acceptable critical ratio values and significance levels. It shows that model variables have a significant impact, and all proposed hypotheses in the model are true.

4.7 Importance performance map analysis (IPMA)

To comprehend the importance and performance of predictors in the model, the author conducted the Importance Performance Map Analysis (IPMA) (Esmailpour et al., 2020; Varma, 2018). As depicted in Fig. 5, the performance in percentage is portrayed on the vertical axis, while importance values are labelled through the horizontal axis. The average values of performance and importance resulted in 74.13% and 0.209, correspondingly. As per inferences, the performance percentage with importance values of 05 predictors were concluded as PI = 72.87% (0.313), CSE = 73.18% (0.289), FC = 76.01% (0.138), PU = 72.41% (0.170) and SDLR = 76.129% (0.135). SDLR and FC performance values are higher than other predictors, while the importance values of PI and CSE are elevated among model variables. The partition of the IPMA chart into four regions was applied with an upper-right section as region-1, lower-right as region-2, lower-left as region-3, and upper-left as region-4 (Ooi et al., 2018). The predictors in region-1 are of higher performance with a higher level of importance, however, no variable from the model existed in this region. Region-2 possesses the most significance and attention from authorities as those variables with higher importance but with lower performance are calculated here likewise two predictors of the model, i.e., PI and CSE. The region-2 should be given more attention and prominence, followed by regions 1, 3, and 4 (Varma, 2018). Hence in this study, attention should be given to PI and CSE to develop the SDL behavior towards digital competence.

4.8 Artificial neural network (ANN)

Surveyed data have certain forms of limitation like non-linearity and distribution normality. PLS-SEM is considered a feasible solution for the non-normal distribution of data, however, to understand the linear and non-linear relationships in surveyed model variables, the structural equation modelling approaches cannot effectively address the non-linearity of data (Leong et al., 2020a). Towards managing the data's non-linearity, the Artificial Neural Network (ANN) method is deemed a suitable solution in numerous fields of study (Liébana-Cabanillas et al., 2017, 2018; Sharma et al., 2019; Sohaib et al., 2020). ANN is novel artificial intelligence (AI) approach to human behavior data analysis, and it has advantages over traditional multivariate regression techniques by deducing the linearity and non-linearity of data. ANN is based on the "black-box" operation, which is unsuitable for testing the hypotheses, however, combining the PLS-SEM and ANN provides the potency of both techniques to comprehend meaningful inferences for the expert system. In SEM-Neural hybrid analysis, initially, hypothesis testing is completed by using PLS-SEM then significant path relationships (i.e., accepted hypotheses) in the model are followed by ANN procedures. To test the ANN for surveyed data, the multilayer perceptron tool was used in SPSS Statistics 24.0 as validated by previous studies (Leong et al., 2020a, b). The sampling data was classified as 90% training and 10% testing. As more data is allocated to the training segment, the improved model prediction result will attain (Hizam et al., 2021); therefore, 90% of data was allocated

Table 5 Hypothesis results

Hypothesis		Path coefficient	C.R.	P	Result
H1	PU→BI	0.170	2.972	0.003	Accepted
H2	FC→BI	0.138	2.661	0.008	Accepted
H3	SDLR→BI	0.135	2.465	0.014	Accepted
H4	PI→BI	0.313	4.491	0.000	Accepted
H5	CSE→BI	0.289	4.633	0.000	Accepted

for training the sample, and 10% of data was assigned to test the sample. The algorithm used for analysis was "feed-forward-back propagation (FFBP)". This FFBP algorithm of ANN is a kind of machine learning process which lowers the number of inaccuracies. ANN is based on 03 layers input, hidden, and output ones, where input layers are termed as neurons, i.e., significant independent variable from PLS-SEM hypothesis analysis, while output layer is a dependent variable from PLS-SEM as illustrated in Fig. 4. As per analysis, all predictors of the PLS-SEM model resulted in significant values; therefore author added all predictors as the neurons in the input layer. To avoid the over-simplification issue, the author conducted the 10-fold cross-validation of ANN models. RMSE (root mean square errors) values for ANN model fit were also calculated for ten-ANN models, as illustrated in Table 6. The RMSE values for the tested sample and trained sample were calculated separately, and it was found that the average RMSE value is relatively low (i.e., RMSE < 0.10), which depicts a good model fit (Leong et al., 2020a). In the next phase, sensitivity analysis of ANN models was conducted to measure the best predictor of behavioral intention.

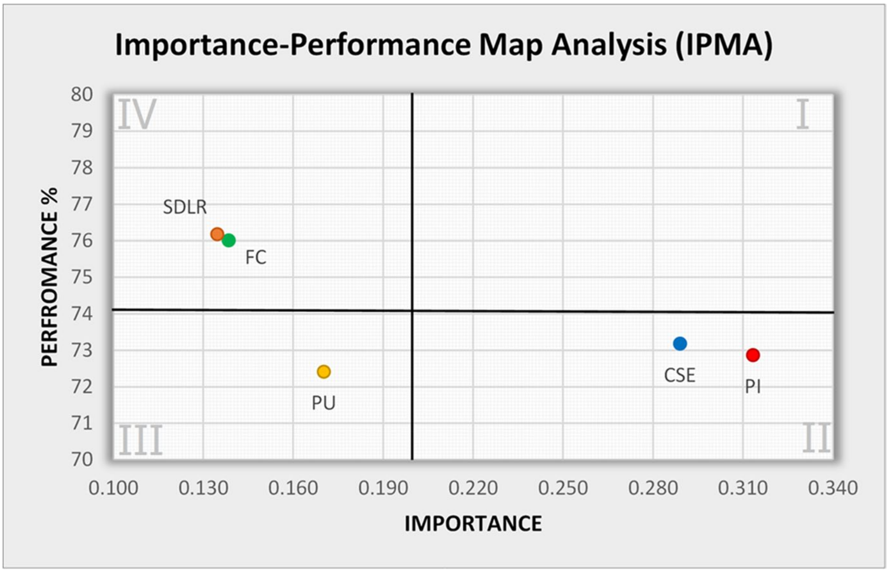


Fig. 5 Importance Performance Map Analysis

Sensitivity analysis depicts the normalized importance where relative importance is divvied by the largest relative importance and portrayed in percentage. As per Table 7, PI has 100% normalized importance which shows PI as the most substantial predictor, followed by CSE (69.57%), FC (37.40%), PU (37.31%), and SDLR (20.21%). Towards describing the predictors' impact on a dependent variable, normalised importance and regression weights are similar in nature.

In Table 8, the comparison of predictors' rank between SEM and ANN elaborated that personal innovativeness is the most significant predictor of BI. Similarly, CSE ranked 2nd in both analyses. PU and FC at rank 03 and 04, respectively, in PLS-SEM but did not match ANN rank. SDLR rank is the same in both analyses' results. The difference in predictors (i.e., PU and FC) rank shows that artificial neural network has the potency to calculate the linear and non-linear associations among independent variables with higher prediction and analytical precision.

5 Discussion

The study's objective was to elucidate the determining factors of SDL behavior toward digital competence among research scholars. For this purpose, a theoretical research framework was outlined, and hypotheses were proposed. Then, data were collected through a survey and evaluated using a multi-analytical approach of SEM-Neural analysis. Before this approach, data were initially tested for common-biased method (CMB) issues. After reporting no data bias, Structural Equation Modelling (SEM) analysis was computed in two phases, namely measurement model (to test data reliability, validity, and factor loadings) and path analysis (to test the proposed hypotheses). Then Importance Performance Map Analysis (IPMA) was analyzed to rank the predictor on performance and their respective importance in the model. Finally, Artificial Neural Network (ANN) analysis was conducted to conclude the model results and compare these with SEM inferences for ranking the predictors.

The inferences showed that behavior to engage in self-directed learning for digital competence is predicted by personal innovativeness (PI), facilitating condition (FC), SDL readiness (SDLR), computer self-efficacy (CSE), and perceived usefulness (PU). The PLS-SEM analysis demonstrated that these variables impacted the business research students' behavior by around 48% (i.e., $R^2 = 0.477$, as shown in Fig. 3) to involve in the SDL process to gain digital competence. The multi-analytical approach, i.e., PLS-SEM, ANN, and IPMA, to understand the predictors of behavioral intention for SDL, provided a novel contribution to literature and practice. This hybrid analysis covered the gap of SEM analysis (i.e., ineffective towards non-linear relationships) and ranked the predictors through normalized importance. Moreover, the advent of IPMA in the SEM-Neural technique presented the chart to categorize the predictors of performance with importance level towards SDL behavior.

Table 6 RMSE values of 10 ANN models

ANN model	SSE		Samples distribution (N=214)		MSE		RMSE	
	TR.	TS.	TR. (90%)	TS. (10%)	TR.	TS.	TR.	TS.
1	1.963	0.076	198	16	0.0099	0.0048	0.0996	0.0689
2	1.384	0.167	187	27	0.0074	0.0062	0.0860	0.0786
3	2.303	0.03	205	9	0.0112	0.0033	0.1060	0.0577
4	1.482	0.181	191	23	0.0078	0.0079	0.0881	0.0887
5	1.522	0.108	188	26	0.0081	0.0042	0.0900	0.0645
6	1.41	0.179	190	24	0.0074	0.0075	0.0861	0.0864
7	1.544	0.127	191	23	0.0081	0.0055	0.0899	0.0743
8	1.306	0.2	190	24	0.0069	0.0083	0.0829	0.0913
9	1.422	0.164	196	18	0.0073	0.0091	0.0852	0.0955
10	1.699	0.145	194	20	0.0088	0.0073	0.0936	0.0851
RMSE Avg							0.091	0.079
RMSE SD							0.0072	0.0125

SSE Sum of Squares Error, *TR* Training, *TS* Testing, *MSE* Mean Squares Errors, *RMSE* Root Mean Square Errors

5.1 Hypothesis results

In hypothesized research framework, the first hypothesis, i.e., PU influences the BI, was significantly supported with a path coefficient of 0.170 and a critical ratio (or t-statistics) value of 2.972. The result is consistent with the previous studies (Gokcearslan, 2017; Hsu & Yeh, 2017). It portrayed that students' intention to self-learn digital tools and techniques will boost once they find this process will enhance their productivity in the research process. The second hypothesis, FC influences the BI, was supported with a path coefficient value of 0.138 and the t-statistics value of 2.661, and this result is also consistent with literature work (Lai, 2013; Marsh, 2018; Sedek et al., 2015). It indicated that ample time, university resources, colleagues' support, and professors' advice are the facilitating conditions for building the capacity to engage in SDL behavior. The third hypothesis, SDL Readiness positively influences the BI, was supported with a path coefficient value of 0.135 and

Table 7 Sensitivity Analysis

Variable	Average importance	Average normalized importance
PU	0.1373	37.31%
SDLR	0.1096	20.21%
CSE	0.2638	69.57%
FC	0.1378	37.40%
PI	0.3847	100.00%

Table 8 Predictors ranking in SEM & ANN models

Variable	Path Coefficient	SEM rank	Average normalized importance (%)	ANN rank	Matched
PI	0.313	1	100	1	**YES**
CSE	0.289	2	69.57	2	**YES**
PU	0.170	3	37.31	4	**NO**
FC	0.138	4	37.40	3	**NO**
SDLR	0.135	5	20.21	5	**YES**

a t-statistics value of 2.465. This hypothesis' result confirmed that self-regulation, discipline, and self-control are aspects of students learning personality, which significantly affect their behavior. This hypothesis inference is steady with the previous surveys (Lin et al., 2016; Zhoc & Chen, 2016). In the fourth hypothesis, PI influences the BI, which emerged as positive and significant, is consistent with previous studies (Geng et al., 2019; Joo et al., 2014; Karimi, 2016). It showed a relatively higher anticipated path coefficient value, i.e., 0.313, and a t-statistics value of 4.491. The plausible explanation is that an innovation-friendly mindset supports the idea of being digitally literate in business research studies. It also implied that an innovative personality enhances the perception of the effectiveness of learning outcomes. The fifth hypothesis, CSE positively impacts the BI, was also supported with a path coefficient value of 0.289 and a t-statistics value of 4.633 and consistent with past research (Chen, 2013; Compeau & Higgins, 1995; Liao et al., 2018). CSE enables the students to make use of technological handling effectively. The more confidence and control in dealing with complex information technology situations, the higher the level of learning motives.

5.2 SEM-Neural and IPMA results

According to SEM-Neural results, see Table 8, among model variables, the role of PI was prominent in both SEM-Neural analyses by grasping the first rank (i.e., 100% average normalized importance in ANN). The IPMA chart, see Fig. 5, places PI in the lower-right section (i.e., region-2) with an averagely less performance (72.87%) and the highest importance level (0.313). It means personal innovativeness is the key to shaping the research scholar's digital competence. Universities and research professionals can comprehend this innovativeness level by creating a pool of research scholars according to their creativity level and being open to innovative ways in their daily lives. Then in return, there will be a group of visionary individuals who are not only digitally proficient but can work on new and creative research ideas that can support the prosperity of society and academia.

The placement of BI and CSE in IPMA showed less performance and higher importance. Likewise, the influence of CSE on BI was ranked second in both SEM and ANN results, while IPMA pinned it in the lower-right section (i.e., region-2). Both predictors can impact the BI at a higher pace, but their performance percentages are less than the average values in IPMA. Computer Self-Efficacy, the second prominent predictor, instigates the stakeholders to enhance the computer training programs for research scholars. The interaction of the non-technical individual with a complex computer program creates an unpleasant situation that hinders the learning process. A researcher with an innovative mindset, integrated with essential computer program handling, can become the progression of the business research process in universities. Such researchers can influence their peers and young fellows in the research community to fortify their skills and competencies.

The ranking of predictors with importance-performance levels explored the impact of PU on BI was calculated with 37.3% of average normalized importance. IPMA inferences showed that PU lies in the third region, a lower-left section on the chart where performance (72.41%) and importance level (0.170) were below the average values of all variables. Next, PU also ranked third as the predictor in PLS-SEM analysis but grabbed fourth place in the ANN model, possibly due to non-linear relationships in the data. Perceiving the usefulness of the SDL process for digital competence can be developed by circumstances and peer influence.

Similarly, FC's effect on BI resulted in 37.4% of average normalized importance and ranked third in the ANN model compared to the fourth position in PLS-SEM analysis. The IPMA placed the FC in the fourth region (i.e., upper-left section), which shows that FC has less importance (0.289) but higher performance (73.18%) towards BI. The facilitating conditions can develop a higher performance level towards developing SDL behavior. Therefore, complementary accessories, processes, and guidance would benefit research students. University and government educational bodies should focus on providing the facilitating infrastructure for the research process. As in this research, most respondents belonged to developing nations from Southeast Asia to South Asian territories recognized as middle-income or upper-middle-income economies. The stakeholders should ponder creating efficient resource allocation for young research scholars to access the research resources such as software, learning modules, and research library subscriptions.

The PLS-SEM and ANN models graded SDLR at the fifth position in the predictors rank, and IPMA showed SDLR as the highest performant (76.129%) with the least importance (0.135) by labelling it in the fourth region. FC and SDLR, being in the upper-left section, have higher performance, which is a positive sign. Still, consideration should be given to their importance level to formulate the behavior towards SDL.

5.3 Research findings

The findings of this study steadily correspond with the literature that supports the role of an individual's psychological arbitrations in understanding learning behavior (Lai, 2013). The study contributes to the knowledge by conceptualising a research framework for crafting SDL behavior toward digital competence, a novel idea that remained inattentive in previous studies. The research work incorporated the business research students in study design which was not considered in prior behavioral studies for technology integration and learning system. To manage the learning mechanism of research scholars, the predictors yielded as cognitive and situational factors. Among these elements, innovativeness (PI) and efficacy (CSE) demonstrated the larger and more significant impact on SDL behavior. Here PI and CSE's role depicted that ambitious students with potential technical skills are better learners than others in business research mechanisms. The duo of PI and CSE was called Digital Dexterity in behavioral study toward digital transformation (Ahmed et al., 2020). There was no empirical validation of Digital Dexterity in extant literature. To a certain extent, this study has empirically validated the role of Digital Dexterity in learning behavior decisive in the technological environment.

Previous studies on SDL and digital competence did not focus on detailed analysis techniques for better and more accurate inferences, like SEM-ANN modelling, to understand the linear and non-linear associations in the model. This study incorporated linear and non-linear relationships between CSE, PI, PU, FC, and SDLR with BI. The machine learning approach (i.e., ANN) trains the sampled data to integrate the best possible prediction scenarios. Therefore, the ranking disparity between multiple regression (i.e., SEM) and 10-fold cross-validation of ANN models (i.e., Neural) is demonstrated in Table 8. Additionally, IPMA structured the latent variables in the chart to support the researchers in conscripting the significant predictors and factors that need more attention. It also helps the scholars to plan the studying elements for future work on this importance-performance matrix of IPMA. According to the IPMA chart, academic and skill development professionals will comprehend the clear idea of important versus performant variables. The emphasis on personal innovativeness and computer self-efficacy is comprehensible for business research students. The urge to enhance their performance by orchestrating a feasible environment of creativity and innovation in academia is apparent. Moreover, this is the first study discussing digital competence elements in the research process. This study also administers that competence is vital for young scholars in today's tech-integrated environment to keep on with the validity of research work.

5.4 Practical implications

This study proposes that academic experts should support business students in boosting their technology efficacy to excel in their research expertise in the digital arena. The business research instructors should focus on building self-control and self-discipline in students towards the learning environment as it shapes the individuals' personality to adopt self-directed behavior in the learning mechanism. The research also suggests that universities breed the learning environment by providing facilitating conditions in terms of resources to develop SDL behavior among students. Such resources entail access to digital libraries, devices, books, and premium research tools such as SPSS Statistics, AMOS, and SmartPLS. Data collection presented a broad spectrum of learning behavior scenarios about business students from numerous developing countries. The multi-analytical inferences explored the ranking of prominent predictors to support the SDL strategy formulation. Moreover, the effective process of SDL towards digital competence in business research students entails a hybrid SDL typology by considering the mutual role of institutions and students. A mandatory learning environment provided by the scholar's organization will enhance the inception of the self-learning arena among students. Then gateway opportunities (i.e., synergistic SDL) could be identified by the inspired learners to step onwards for the knowledge development process. Doing so will boost the behavior of self-consideration of opportunities towards the goals (either with a definite finish point, i.e., voluntary SDL or no predetermined end, i.e., scanning SDL). A hybrid strategy of Synergistic SDL and Scanning SDL directs the suitable approach to understanding the SDL behavior among business research students.

Digital literacy is similar to technology acceptance for research work, but digital competence is deducing the fruitful implication of that technology to enhance the efficiency of research work. Contemplating the digital competence framework for business research scholars is an inventive contribution of this study which was not pondered in previous literature. Gone are those days when researchers had to consult the libraries, vast volumes of paper notes, and stick around the mentors and colleagues to enhance the research collaboration. The prevailed emergence of digital transformation in daily life craved devising the pertinent skill framework for researchers. The proposed digital competency framework (as shown in Fig. 1) will help the scholars build their expertise for a smooth research process. Academic professionals can use this framework to engage early career scholars at enrollment. A particular form of skill assessments, evaluation, and training can be conducted to formulate the high performant research experts with tech-savvy profiles by the university research society.

5.5 Theoretical contribution

From a theoretical point of view, numerous studies investigated either SDL behavior or digital competence towards learning perception. Far less attention was paid to crafting SDL behavioral model toward digital competence. Moreover, the previous literature was also unfamiliar with research on SDL behavior toward scholars' digital competence with a robust theoretical framework. This study establishes a new research model with five predicting elements from cognitive and circumstantial scenarios (Perceived Usefulness, Personal Innovativeness, Computer Self-Efficacy, Facilitating Conditions, and Self-Directed Learning Readiness). It has provided a novel dimension to understanding young scholars' decision to engage in SDL process toward digital competence. Among these elements, Personal Innovativeness and Computer Self-Efficacy portrayed the paramount significance of regulating such behavior towards becoming digitally competent. As adopted from TAM and UTAUT models, these theoretical dimensions also proved a robust and validated model for technological interaction and integration in learning sciences. This research work has also signalled the soundness of the novel concept of Digital Dexterity through Personal Innovativeness and Computer Self-Efficiency. The study has also filled the theoretical gap by inducing and validating the two-stage multi-analytical scheme of SEM-Neural. The induction of IPMA in SEM-Neural is also one of the distinctive features of the study.

5.6 Limitations & future recommendations

The proposed research framework is limited to assessing learners' behavior through quantitative measurements, while future work can include the instructors and supervisors as study phenomena. Future studies about the assessment of SDL behavior would provide a better conclusion thru a qualitative lens of measurements. Steering qualitative approach or mixed method might also have explored a broad spectrum of behavioral patterns in open-ended questions, interviews, and detailed observations. As the study included a limited number of psychological factors in behavioral assessment, the forthcoming studies would add more factors such as social influence, advanced computer literacy, digital citizenship, and learning dimensions for more distinct inferences. This study entailed the ANN method, inferred the data results through one hidden layer, and kept the training and testing data at 90% and 10%, respectively. The results could be different in future work when adding multiple hidden layers and varying the training and testing data percentages. The study practised the convenience sampling method in the data collection process with generalizability limitations, lack of simplicity, and error-avoid scenarios. Future studies would be more pertinent to understanding behavioral assessment by following the probability sampling techniques and categorizing the analysis on a demographic basis. As this study was conducted online with respondents from multiple universities and countries, future studies can comprehend such analysis either at a single institution or multiple universities to explore and compare the SDL behavior patterns for digital competence among enrolled students.

Data availability statement The datasets for this research work will be available from the author upon reasonable request.

Declarations

Conflict of interest statement There is no conflict of interest to declare.

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