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COVID-19: Job insecurity as a moderator of e-learning acceptance in Indian organisations

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Orientation: Coronavirus disease 2019 (COVID-19) pandemic caused the loss of jobs of more than 340 million individuals worldwide in the middle of 2020. At the same time, COVID-19 pandemic sparked increased usage of digital products, Internet resources, online media technology and e-learning practices.

Research purpose: The research strives to explore the moderating role of job insecurity caused by the coronavirus towards the usage of e-learning.

Motivation for study: This study aimed to assess the behavioural effects of employees working in the most damaged sectors related to rental and business services of Indian businesses.

Research approach/design and method: The investigation used a structured questionnaire for the survey data obtained from 307 employees from the most affected sectors in major cities of India. The research utilised the conservation of resources (COR) theories and the General Extended Technology Acceptance Model for e-learning (GETAMEL) framework for the investigation. To probe the evidence, the researchers used Structural Equation Modelling techniques.

Main findings: The findings revealed a substantial impact of 'job uncertainty' as a moderator in employees' acceptability towards e-learning.

Practical/managerial implications: The study provides a deep insight to experts, educators, top management, policymakers, team managers and human resource (HR) practitioners about the moderation effect of job insecurity created by pandemics on technology acceptance.

Contribution/value add: This study is unique as no researcher investigated the moderating influence of job instability on e-learning acceptability.

Keywords: GETAMEL; job insecurity; behavioural intention; e-learning; COVID-19.

Introduction

The coronavirus pandemic (COVID-19), as per the International Labour Organization-Asian Development Bank (ILO-ADB, 2020), has caused severe chaos in businesses and job markets worldwide, with terrible effects on employment in youth. As per recent projections from the International Labor Organization (ILO, 2020), the pandemic might cause job loss for more than 340 million individuals worldwide in the middle of 2020. At the same time, the COVID-19 pandemic has sparked increased usage of digital products, Internet resources, online media technology and e-learning practices (Basilaia & Kvavadze, 2020). This research strives to figure out how they interact in the perspective of surging job insecurity and mandatory technology adoption.

Relevance of context

In Asia and the Pacific, the worst COVID-19-affected sectors are: (1) rental and business services, (2) retail and wholesale trade, (3) accommodation and food services and (4) manufacturing and repair services, employing nearly 50% of the younger generation (exceeding 100 million) at the advent of COVID-19 (ILO-ADB, 2020). Therefore, the authors identified the necessity for a study to assess the behavioural effects on employees working in the most damaged sectors related to rental and business services of Indian businesses.

Rationale

In the COVID-19 scenario, the primary sufferers were workers whose livelihood was severely affected by COVID-19 along with historic numbers of furloughs and layoffs worldwide (Hamouche,

2020) and higher rates of unemployment (Congressional Research Service [CRS], 2021), for example, Europe (6.0%), the Americas (2.7%) and Arab States (1.7%). The study was undertaken at a time of worst job scenario conditions and the worst psychological behaviour of employees in India, which makes the study unique compared to the other studies. During the current pandemic, e-learning is more like compelled learning than planned learning (Bao, 2020). It is therefore required to understand how mandated e-learning might combat employment insecurity caused by COVID-19. Despite numerous studies on work insecurity and e-learning adoption, no researcher investigated the moderating influence of job instability on e-learning acceptability. Moreover, the authors found no research on e-learning acceptability in the pandemic scenario in India. This paper fills the identified research gap in the body of knowledge.

The key objectives of the investigation are as follows.

- To re-validate the General Extended Technology Acceptance Model for e-learning (GETAMEL) in the present COVID-19 scenario.
- To look into the effect of job insecurity caused by COVID-19 as a moderator.

Theoretical base

Preliminary literature

The GETAMEL framework and the conservation of resources (COR) theory serve as the research framework's foundation. Conservation of resource theory is based on three crucial tenets. As per COR theory's fundamental tenet, resource loss is disproportionately more significant than resource gain. The second tenet of COR theory is that in order to guard against resource loss, make up for losses and acquire resources people must spend resources. The third tenet of COR theory is paradoxical. It argues that resource advantage becomes more significant when resource depletion is prevalent. After thoroughly assessing 107 existing research publications regarding e-learning, Abdullah and Ward (2016) formulated the GETAMEL framework for e-learning acceptability. Among the 152 distinct external variables evaluated in the 107 researches, Technology Acceptance Model (TAMs) confirmed and most often used external factors were: (1) experience, (2) enjoyment, (3) subjective norm, (4) computer anxiety and (5) self-efficacy (Davis, 1989). They realised these five widely exploited and proven external variables in their suggested GETAMEL approach. Moreover, the model is specific to e-learning adoption. Consequently, in the existing COVID-19 scenario, the study used and enhanced the same model based on literature recommendations.

In the COVID-19 scenario, the authors utilised the COR mechanism and the GETAMEL model to establish the affinity of job insecurity to behavioural response to e-learning. The current study uses the first investigation applying COR theory to assess the COVID-19 impact using the GETAMEL model. Many factors favour COR postulations as a defence strategy over other theories. The COR theory is widespread stress and motivational theory, so the authors found it suitable for the impact of COVID-19-related job insecurity on behavioural response (Hobfoll, 2001). Moreover, the conceptual model used in this study mentions the acquisition and forfeiture of resources. To the researcher's knowledge, the extant literature is mute regarding COVID-19's involvement in changing employee perception of e-learning, except for a few studies (Bhatt & Shiva, 2020; Elahi et al., 2021). Conservation of resource postulations, the authors believe, better match their suggested framework than the other theories.

Research hypotheses

Behavioural intent to use

Behavioural intent is the estimated chances of an individual participating in a specific conduct (Fishbein & Ajzen, 1975, p. 288). The current study identified perceived usefulness, perceived ease of use, computer anxiety, perceived enjoyment, computer self-efficacy, subjective norms and job insecurity as critical determinants of behavioural intent for e-learning adoption. The determinants of behavioural intent are essential to understand because of the atmosphere of mandatory e-learning acceptability.

Perceived usefulness and perceived ease of use

The TAM used in the research studies comprised two key predictors – perceived ease of use (PEOU) and perceived usefulness (PU). Past studies (Adenuga et al., 2019; Davis, 1989; Salloum et al., 2019; Venkatesh & Bala, 2008) explained the prominence of these variables.

Perceived ease of use characterises the amount a person conceives about employing a specific entity without any stress on the brain. On the other hand, PU relates to how a person envisions improved work performance after using a given entity (Davis, 1989, p. 320). Past studies (Bhatt & Shiva, 2020; Kamal et al., 2020; Rizun & Strzelecki, 2020; Tarhini et al., 2017; Venkatesh & Bala, 2008) have established that PU and PEOU positively influenced behavioural intention (BI) to utilise e-learning. Khan et al. (2020) advocated a longitudinal study because users' perceptions of the utility and convenience of online learning may change over time (Ching-Ter et al., 2017). There is a need to re-validate the relationship between PEOU and BI. When employees feel that e-learning mechanisms are simple to use and that their use would improve their learning performance, their intention to utilise them will increase. As a result, the authors undertook the following hypothesis:

H1: The measures of control PU influence BI positively.

H2: The measures of control PEOU influence BI positively.

Perceived enjoyment

Perceived enjoyment characterises 'the amount with which the action of utilising a certain system is deemed delightful in and of itself, regardless of any performance implications resulting from system usage' (Venkatesh, 2000). Based on previous studies (Elkaseh et al., 2016; Rizun & Strzelecki, 2020), the authors hypothesised that when employees perceive an e-learning methodology as pleasurable, it is more likely to have a favourable influence on behavioural intent to utilise it. As a result, the authors came up with the following hypothesis:

H3: The measures of perceived enjoyment (PEJ) influence BI positively.

Computer anxiety

Computer anxiety refers to 'the amount of a person's trepidation, or even panic when presented with the idea of using computers' (Venkatesh, 2000). Previous studies (Igbaria & Parasuraman, 1989; Rifa & Gudono, 1999) have established a significant influence of computer anxiety on employees' behaviour towards adoption of e-learning. Based on previous studies, the authors assumed that individuals with lesser computer anxiety have greater technical proficiency and a stronger behavioural intent to utilise e-learning. As a result, the authors came up with the following hypothesis:

H4: The measures of e-learning anxiety would have a considerable negative impact on BI.

Computer self-efficacy

Computer self-efficacy (CSE) is 'the amount to which a person thinks she/he can execute a particular job through the computer' (Compeau & Higgins, 1995). Based on previous studies (Abbasi et al., 2015; Vijayasarathy, 2004), the authors hypothesised that individuals comfortable with computers will find technology simple and should have a favourable perception of it. Thus, the authors came up with the following hypothesis:

H5: The e-learning self-efficacy indicators have a favourable impact on BI.

Subjective norm

Subjective norm (SN) is a person's perspective that the main characters of his life feel whether an individual should or should not do in a specific manner (Venkatesh et al., 2003). Few investigations have shown the substantial influence of SN (Venkatesh & Davis, 2000; Venkatesh et al., 2003), whereas others (Chau & Hu, 2002; Lewis et al., 2003) found no linkage between SN and BI. The following hypothesis has been added after seeing the contradiction in the current literature:

H6: The measures of subjective norm would have a considerable positive influence on BI.

Computer experience

Computer experience (XP) is 'the extent and nature of an individual's computer abilities over time in work' (Rizun & Strzelecki, 2020). Based on previous studies (Rizun & Strzelecki, 2020; Vijayasarathy, 2004), the authors hypothesised that more experienced users are more prone to utilise e-learning. Therefore the authors adopted the following hypothesis:

H7: The measures of e-learning experience would have a considerable positive impact on BI.

Job insecurity

Job insecurity is 'the perception of a threat toward an individual's existing job's continuance' (Heaney et al., 1994). The current study applies the COR postulations proposed by Hobfoll (1989) for building the remaining hypotheses. Resource loss is the most crucial component in forecasting the psychological consequences of distressing events (Hobfoll, 1989, 2001). Resources are objects, people's attributes, situations or energies that are valuable in and of themselves or because they behave as channels for acquiring or preserving valuable resources (Hobfoll, 1989). Coronavirus disease 2019 created an atmosphere of job insecurity (ILO, 2020). This process is consistent with the COR postulation: job insecurity is a prime example of energetic resource depletion leading to more resource loss, such as job insecurity. Job insecurity causes a loss of resources, leading to a protective attitude and consuming more resources while slowing the growth of other resources. Job insecurity can proactively steer people's behaviour and processes to safeguard resources or recoup from forfeiture of resources (Hobfoll et al., 2006). According to the COR model, avoidance of loss spirals is possible even if an organisation introduces brief periods of gain at some time. The authors propose that e-learning serves as a substantial personal resource that aids individuals in regaining and retaining their resources, based on COR theory (job loss). After stating e-learning is a unique resource (Hobfoll, 2001), the authors suggest that a greater degree of COVID-19-related job insecurity leads to a high behavioural intent to utilise e-learning. As a result, the authors formulated the hypothesis as follows:

H8: The measures of e-learning job insecurity would have a considerable positive impact on BI.

Based on COR theory, resource drain in the perspective of job insecurity motivates the constructs of antecedents of BI, which can be stated in the form of hypotheses as mentioned below:

H1a: Job insecurity moderates the linkage of PU to BI.

H2a: Job insecurity moderates the linkage of PEOU to BI.

H3a: Job insecurity moderates the linkage of perceived enjoyment to BI.

H4a: Job insecurity moderates the link of computer anxiety to BI.

H5a: Job insecurity moderates the link of self-efficacy to BI.

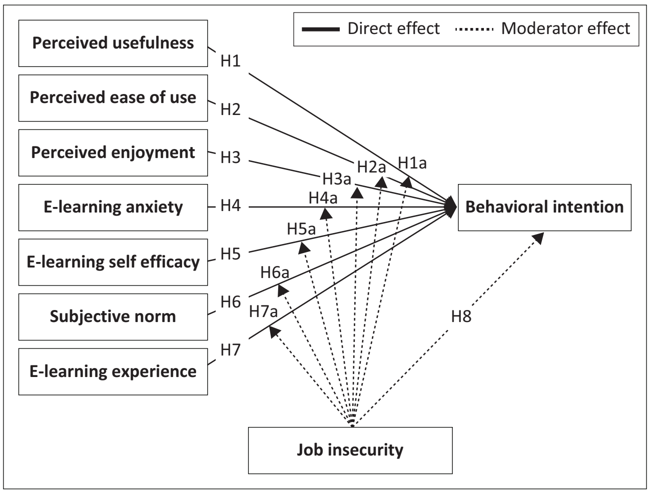
H6a: Job insecurity moderates the linkage of subjective norms to BI.

H7a: Job insecurity moderates the linkage of computer experience to BI.

Figure 1 depicts the proposed hypotheses in diagrammatic form.

Research design

The current study adopts a positivist philosophy as per the classification of Orlikowski and Baroudi (1991). The



Source: *Derived from GETAMEL model* Abdullah, F., & Ward, R. (2016). Developing a General Extended Technology Acceptance Model for E-Learning (GETAMEL) by analysing commonly used external factors. *Computer in Human Behavior*, 56(1), 238–256. https://doi.org/10.1016/j.chb.2015.11.036

FIGURE 1: Proposed research model.

formal propositions established through literature review, operationalisation of quantifiable constructs, the testing of hypotheses and generalisation are all examples of positivist shreds of evidence that form the blueprint of the study. As the authors used a quantitative and a qualitative study to support their findings, a mixed method technique was used in this research. Little qualitative research helps guide data gathering in a primarily quantitative investigation, generate ideas and produce material for questionnaires.

Data collection and employee sample

The study's online survey methodology was adopted through a 38-item question sheet. Non-probability sampling was used, viz., the purposive sampling approach to select the sample. Data was collected from the rental and business services employees in major Indian cities from September to December 2020. The final sample consisted of 307 employees. Data are collected online (N = 247) and in hard copy format (N = 160). Out of the total responses received, 100 responses were because of missing values in the gathered data. Harman's single-factor test was applied to the final data collected to verify the evidence of common method bias (Podsakoff et al., 2003). The first unrotated factor recorded only 25.4% data variance, suggesting no common method variance (CMV) issue in the current investigation.

Measures

The survey was divided into two sections: a section for employees' demographic characteristics, followed by a questionnaire for measuring the study's 10 constructs. A total of 38 statements were employed to gauge the nine constructs: PU, PEOU, PEJ, CSE, computer anxiety (CA), SN, XP, BI and job insecurity (JI). All the constructs utilised in this investigation contained items with five-point Likert-type scales varying from '1' indicating strong agreement to '5' indicating strong disagreement. The authors used a three-item scale designed by Adenuga et al. (2019) for assessing the PU for e-learning, a five-item scale designed by Adenuga et al. (2019) for determining the PEOU, a five-item scale designed by Salloum et al. (2019) for assessing the PEJ, a four-item scale designed by Venkatesh and Bala (2008) for evaluating the CA, a five-item scale designed by Salloum et al. (2019) for assessing the CSE, a five-item scale designed by Salloum et al. (2019) for determining the SN, a four-item scale designed by Rizun and Strzelecki (2020) for assessing the XP, a three-item scale designed by Adenuga et al. (2019) for determining the BI and a four-item scale designed by Vander Elst (2014) for assessing the JI e-learning acceptability for the survey. The authors prepared a questionnaire of 38 items and referred to 10 experts in social work practice and academic and industrial management. The authors modified each item and reorganised the questionnaire based on the experts' suggestions and a pilot study of roughly 50 questionnaires.

TABLE 1: Demographic characteristics of employees under study.

Demographic variables	Number of respondents (frequency)	Percentage of respondents
Age in years		
Less than 25	84	27.4
26–34	44	14.3
35–45	95	30.9
Above 45	84	27.4
Company experience		
< 2 years	74	24.1
2 to 5 years	65	21.2
5 to 8 years	87	28.3
Above 8 years	81	26.4
Education		
Diploma	106	34.5
Graduate	181	59
Post graduate	20	6.5
Employment nature		
Permanent	273	88.9
Contractual Deputation	34	11.1
Job role		
Supervisory role	130	42.3
Below managerial role	44	14.3
Managerial role	39	12.7
Above managerial role	94	30.6
Marital status		
Married	254	82.7
Unmarried	53	17.3
Sex		
Male	192	62.5
Female	115	37.5

Data analysis

Amos 21.0 was used to test this investigation's path and postulated model. The authors separated the analysis into two parts to validate the suggested model as per Anderson and Gerbing's (1988) methodology. The first part verified the measurement model for factor analysis, the goodness of fit and construct validity. After achieving a good measurement model, the authors utilised SEM (structural equation modelling) to empirically characterise the structural link between the constructs using path estimations. For hypothesis testing, a three-step multiple hierarchical regression analysis was performed. In the first phase, the authors took all constructs of the GETAMEL model as independent variables with the augmentation of the moderator variable in the second phase and then interaction terms augmented in the third phase.

Ethical considerations

This article followed all ethical standards for research without direct contact with human or animal subjects.

Results

Descriptive information

The demographic characterisation of employees under study are mentioned in Table 1, which includes employees' age, annual income, company experience, education, employment nature, job role, marital status and sex (*N* = 307, male = 192, female = 115).

Measurement model analysis

Performed measurement model analysis with factor analysis using the principal component analysis (PCA) with oblimin rotation on each construct. The Kaiser–Meyer–Olkin (KMO) test was applied to demonstrate factorability, and the KMO values for PU, PEOU, PEJ, CA, CSE, SN, XP, JI and BI are 0.722, 0.904, 0.842, 0.835, 0.853, 0.9, 0.813, 0.836 and 0.748, respectively. The KMO measure validated the sampling adequacy for the assessment; the authors found KMO values for all discrete items and the overall model (overall KMO = 0.886) to be more than the tolerable limit of 0.6 (Tabachnick & Fidell, 2007, p. 619). Researchers carried out the confirmatory factor analysis (CFA) in SPSS-AMOS 21.0 to evaluate the data's fitness to the study's suggested measurement model. As part of the CFA, the authors looked at convergent validity, construct reliability, discriminant validity and goodness of fit statistics.

Indicator reliability

Indicator reliability is the percentage of a single indicator's variance obtained from pertinent latent variables. As demonstrated in Table 2, the standardised estimates for each construct were between 0.76 and 0.94, more than the acceptable threshold of 0.7 recommended by CarmineZs and Zeller (2008). Indicator reliability for each construct is above 0.5 per recommendations (Carmines & Zeller, 1979). The authors employed the bootstrap approach with 5000 samples proposed by Henseler et al. (2009); all item loadings were statistically significant at $p \leq 0.001$ (Henseler et al., 2009). Furthermore, the study instrument's Cronbach's alpha is 0.918 because it exceeds the allowed limit of 0.6 (Hair et al., 2014, p. 125).

Construct reliability

Construct reliability is the 'estimation of the level to which change in the measure echoes variation in the underlying construct,' according to Westen and Rosenthal (2003). Construct reliability establishes convergent validity, content validity and discriminant validity.

TABLE 2: Latent variable with validity and reliability.

Latent variable	Convergent validity			Internal consistency reliability	
	Standard loading (> 0.7)	Indicator reliability (> 0.5)	AVE (> 0.5)	CR (> 0.7)	Cronbach alpha (0.7–0.9)
Perceived usefulness (PU)					
PU01	0.766	0.587	0.656	0.851	0.849 (3)
PU02	0.804	0.646	-	-	-
PU03	0.857	0.734	-	-	-
Perceived ease of use (PEOU)					
PEOU 01	0.868	0.753	0.762	0.941	0.939
PEOU02	0.87	0.757	-	-	-
PEOU03	0.924	0.854	-	-	-
PEOU04	0.928	0.861	-	-	-
PEOU05	0.765	0.585	-	-	-
Perceived enjoyment (PEJ)					
PEJ01	0.88	0.774	0.785	0.948	0.947 (5)
PEJ02	0.921	0.848	-	-	-
PEJ03	0.941	0.885	-	-	-
PEJ04	0.891	0.794	-	-	-
PEJ05	0.789	0.623	-	-	-
Computer anxiety (CA)					
CA01	0.776	0.602	0.683	0.896	0.894 (4)
CA02	0.859	0.738	-	-	-
CA03	0.855	0.731	-	-	-
CA04	0.812	0.659	-	-	-
Computer self-efficacy (CSE)					
CSE01	0.807	0.651	0.678	0.913	0.912 (5)
CSE02	0.87	0.757	-	-	-
CSE03	0.837	0.701	-	-	-
CSE04	0.823	0.677	-	-	-
CSE05	0.777	0.604	-	-	-
Subjective norm (SN)					
SN01	0.864	0.746	0.742	0.935	0.935 (5)
SN02	0.869	0.755	-	-	-
SN03	0.874	0.764	-	-	-
SN04	0.879	0.773	-	-	-
SN05	0.82	0.672	-	-	-
Experience (XP)					
XP01	0.894	0.799	0.755	0.925	0.924 (4)
XP02	0.893	0.797	-	-	-
XP03	0.889	0.790	-	-	-
XP04	0.795	0.632	-	-	-
Behavioural intention (BI)					
BI01	0.889	0.790	0.772	0.91	0.904 (3)
BI02	0.836	0.699	-	-	-
BI03	0.91	0.828	-	-	-
Job insecurity (JI)					
JI01	0.792	0.627	0.649	0.881	0.879 (4)
JI02	0.808	0.653	-	-	-
JI03	0.778	0.605	-	-	-
JI04	0.842	0.709	-	-	-

AVE, average variance extracted; CR, composite reliability.

Content validity

The measures from prior literary works were taken by the authors to ascertain face validity. The authors further modified the scales to suit the requirements of the ongoing investigation.

Convergent validity

The authors performed convergent validity by applying average variance extracted (AVE) and composite reliability

TABLE 3: Mean, SD, Cronbach alpha, KMO value and factor correlation matrix with √AVE values on the diagonal cells.

	Mean	SD	KMO	PU	PEOU	PEJ	CA	CSE	SN	XP	BI	JI
PU	2.569	1.164	0.722	**0.810**	-	-	-	-	-	-	-	-
PEOU	2.820	1.408	0.902	0.256	**0.873**	-	-	-	-	-	-	-
PEJ	2.643	1.249	0.842	0.267	0.123	**0.886**	-	-	-	-	-	-
CA	2.679	1.196	0.835	0.441	0.212	0.158	**0.826**	-	-	-	-	-
CSE	2.830	1.170	0.853	0.117	0.258	0.449	0.093	**0.823**	-	-	-	-
SN	2.617	1.206	0.900	0.188	0.183	0.608	0.123	0.554	**0.861**	-	-	-
XP	2.988	1.173	0.813	0.090	0.186	0.150	0.154	0.130	0.090	**0.869**	-	-
BI	3.047	1.258	0.748	0.324	0.399	0.565	0.197	0.454	0.419	0.261	**0.879**	-
JI	2.882	1.172	0.836	0.049	0.096	0.181	0.124	0.178	0.256	−0.054	0.322	**0.806**

SD, standard deviation; KMO, Kaiser–Meyer–Olkin; PU, perceived usefulness; PEOU, perceived ease of use; PEJ, perceived enjoyment; CA, computer anxiety; CSE, computer self-efficacy; SN, subjective norm; XP, computer experience; BI, behavioural intention; JI, job insecurity.

TABLE 4: Hypothesised results summary.

Hypothesis	Suggested linkage	Model I†			Model II‡			Model III§			Consequence
		std. coeff	*t*-value	*p*-value	std. coeff	*t*-value	*p*-value	std. coeff	*t*-value	*p*-value	
H1	PU(+)->BI	0.13	2.64	0.009	0.14	2.903	0.004	0.123	2.723	0.007	Supported
H2	PEOU(+)->BI	0.248	5.285	0.000	0.24	5.25	0.00	0.264	6.227	0.000	Supported
H3	PEJ(+)->BI	0.369	6.572	0.000	0.36	6.63	0.00	0.294	5.819	0.000	Supported
H4	CA(-)->BI	0.001	0.025	0.98	-0.021	-0.45	0.65	-0.053	-1.22	0.223	Supported
H5	CSE(+)->BI	0.163	3.064	0.002	0.15	2.96	0.003	0.113	2.276	0.024	Supported
H6	SN(+)->BI	0.012	0.198	0.843	-0.025	-0.44	0.66	0.001	0.026	0.979	Not supported
H7	XP(+)->BI	0.116	2.59	0.01	0.136	3.107	0.002	0.157	3.625	0.000	Supported
H8	JI(+)->BI	-	-	-	0.199	4.509	0.000	0.267	6.245	0.000	Supported
H1a	PU*JI(+)->BI	-	-	-	-	-	-	0.16	3.473	0.001	Supported
H2a	PEOU*JI(+)->BI	-	-	-	-	-	-	0.144	3.293	0.001	Supported
H3a	PEJ*JI(+)->BI	-	-	-	-	-	-	-0.085	-1.558	0.12	Not supported
H4a	CA*JI(+)->BI	-	-	-	-	-	-	-0.085	-1.94	0.053	Not supported
H5a	CSE*JI(+)->BI	-	-	-	-	-	-	-0.117	-2.29	0.023	Supported
H6a	SN*JI(+)->BI	-	-	-	-	-	-	-0.086	-1.545	0.123	Not supported
H7a	XP*JI(+)->BI	-	-	-	-	-	-	0.2	4.467	0.00	Supported

†, R^2 = 0.43, Change in R^2 = 0.43, Change in F-value = 31.78, p-value sig (F-change) = 0.00; ‡, R^2 = 0.46, Change in R^2 = 0.037, Change in F-value = 20.33, p-value sig (F-change) = 0.00; §, R^2 = 0.56, Change in R^2 =0.1, Change in F-value = 9.86, p-value sig (F-change) = 0.00.

PU, perceived usefulness; PEOU, perceived ease of use; PEJ, perceived enjoyment; CA, computer anxiety; CSE, computer self-efficacy; SN, subjective Norm; XP, computer experience; BI, behavioural intention; JI, job insecurity.

(CR), as demonstrated in Table 2. The CR values for each measure varied from 0.851 to 0.948, well above Bagozzi and Yi's (1988) suggested criteria of 0.7. The item's AVE values fell in the range of 0.649–0.785, exceeding the acceptable thresholds of 0.5 (Bagozzi & Yi, 1988), indicating high convergent validity.

Discriminant validity

Discriminant validity depicts how the items employed in measurement deviate from one another (Campbell & Fiske, 1959). Table 3 displays the mean, SD, KMO, matrix of factor correlation and √AVE on the diagonal cells. The square root values (√AVE) are larger than the construct correlations, demonstrating that the data have robust discriminant validity, as stated by Fornell and Larcker's (1981) criteria.

For the estimation of the parameters of the model, the maximum-likelihood method is adopted. The measurement model's goodness-of-fit statistics established that it was well-fit to the data ($p < 0.05$; Minimum Discrepancy Function by Degrees of Freedom divided [CMIN/df] = 1.672 [less than 3], Tucker Lewis index [TLI] = 0.95 [> 0.9], Comparative Fit index [CFI] = 0.955 [> 0.9], Normed Fit index [NFI] = 0.9 [> 0.9] and root mean square error of approximation [RMSEA] = 0.038 [< 0.1], standardized root mean square residual [SRMR] = 0.038 [less than 0.08]). Thus, the measurement model exhibits sound construct validity.

Structural model and testing of hypotheses

Table 4 demonstrates the results of the hypotheses tests. Figure 2 exhibits the measurement model displaying the beta coefficients and R^2.

The authors examined the suggested model's goodness-of-fit parameters; the model produced a statistically significant chi-square, χ^2 = 873.16; df = 499; CMIN/df = 1.75; $p < 0.001$. The fit indices were CFI = 0.957, TLI = 0.952, RMSEA = 0.05 and SRMR = 0.0362, which indicated a good model fit. As a result, the authors proceed to investigate the model's hypothesised linkages.

While performing three-stage multiple hierarchical regression, the first stage supports hypotheses H1 to H7 except for H4 and H6. The authors noted PU (β = 0.13; p < 0.01) and PEOU (β = 0.248; p < 0.01) to get a substantial positive effect on BI for the usage of e-learning, strengthening H1 and H2. The influence of PEJ (β = 0.369; p < 0.01) on BI maintains hypothesis H3. Furthermore, CSE

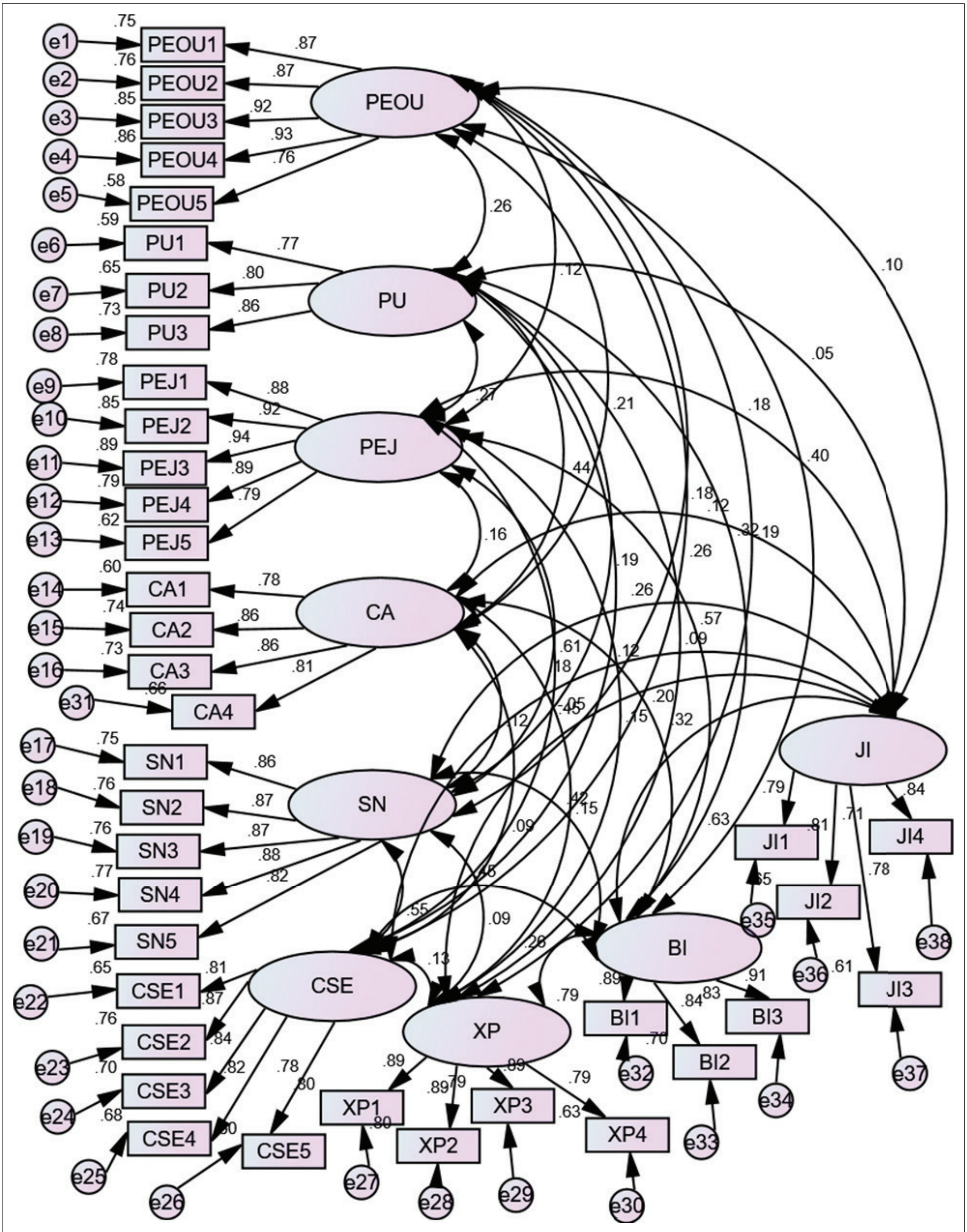


FIGURE 2: Confirmatory factor analysis model.

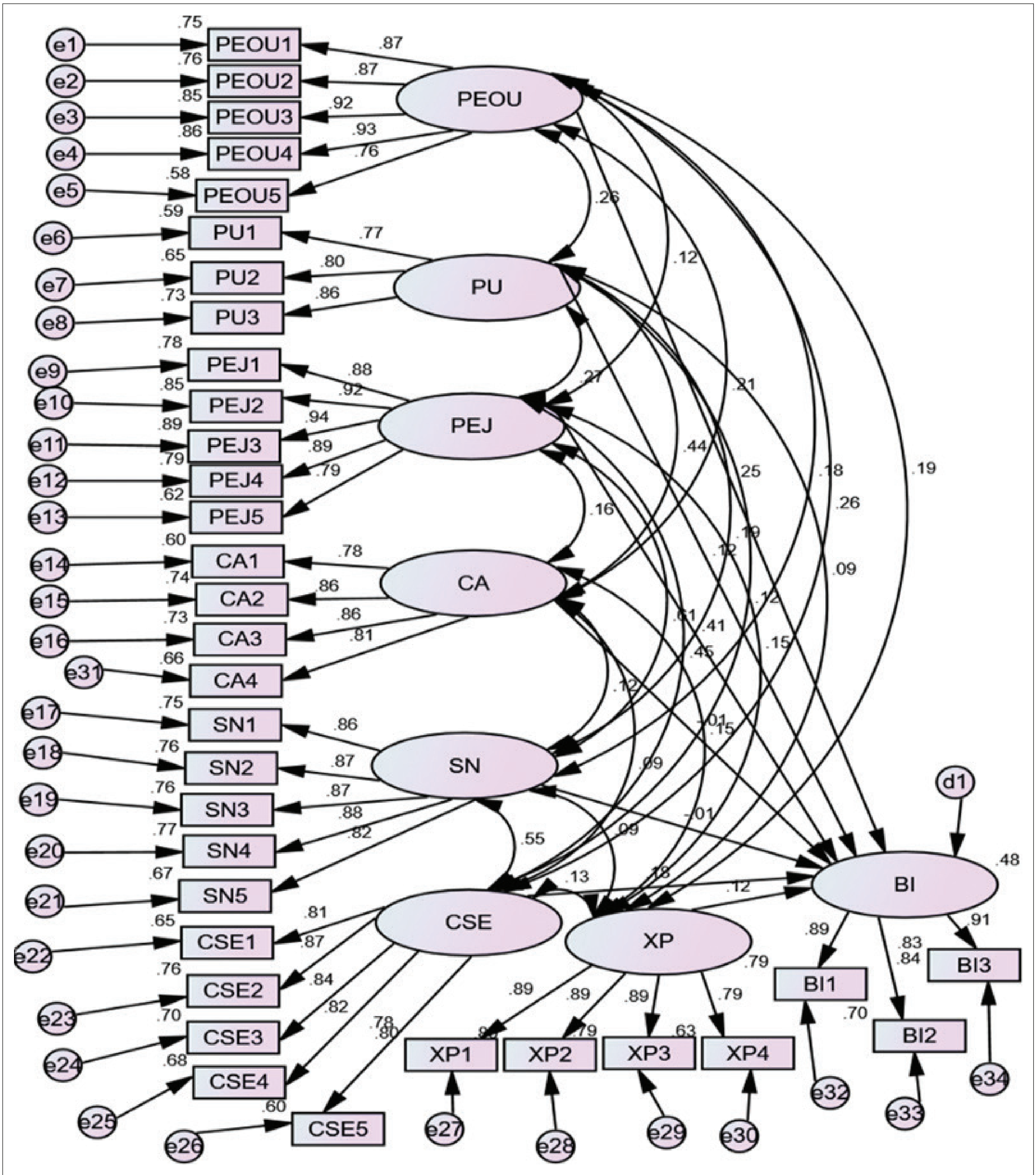


FIGURE 3: Measurement model.

($\beta = 0.163$; $p < 0.01$) and XP ($\beta = 0.116$; $p < 0.01$) influence BI, which supports assumptions H5 and H7. The direct effect of CA ($\beta = 0.001$; p is higher than 0.01) and SN ($\beta = 0.012$; p is at a higher level than 0.01) are not significant, implying that H4 and H6 are unsupported hypotheses. In the second stage, moderator variable JI ($\beta = 0.199$; $p < 0.01$) has reported a substantial positive effect on BI. In the third stage, interaction variables on BI were regressed. Job insecurity moderates the relationship between PU and BI ($\beta = 0.16$; $p < 0.01$), strengthening hypothesis H1a, between PEOU and BI ($\beta = 0.144$; $p < 0.01$), supporting hypothesis H2a, between CSE and BI ($\beta = -0.117$; $p < 0.01$) strengthening hypothesis H5a and XP and BI ($\beta = 0.2$; $p < 0.01$) strengthening hypothesis H7a. The moderating effect of PEJ ($\beta = -0.085$; $p > 0.01$), CA ($\beta = -0.085$; $p > 0.01$) and SN ($\beta = -0.086$; $p > 0.1$) on BI is not found to be significant, which does not support hypotheses H3a, H4a and H7a. The authors took all constructs of the GETAMEL model as independent variables with the augmentation of the moderator variable in the second stage; then, they augmented interaction terms in the third stage.

Predictor variables constituted by basic GETAMEL constructs explain 43%, model augmented by moderator 46% and then interaction terms included 56% of the variance in BI.

Discussion

The first two hypotheses, H1 and H2, suggesting the positive association of PEOU and PU with BI, are compliant with the findings of Tarhini et al. (2017) and Salloum et al. (2019). Hypothesis H3 supports the positive impact of PEJ on BI, which is in synchronisation with Salloum et al. (2019). This study establishes the non-significant association of CA with BI found in hypothesis H4 of the current research, which contradicts the significant negative relation reported by Adenuga et al. (2019). The assumptions H3, H4 and H5 are synchronised with Sriningsih et al. (2018), stating that PEJ and CSE had a considerable influence, and CA had no significant impact on BI. Hypothesis H6 posits that SN does not significantly impact BI, synchronising with Salloum et al. (2019). Hypothesis H7 states that experience (XP) particularly moved BI, synchronising with Rizun and Strzelecki (2020). Therefore the objective of revalidation of the GETAMEL model in the COVID-19 scenario is met.

The results established in hypothesised relationships H1a, H2a, H3a, H4a, H5a, H6a and H7a represent new findings not reported in previous studies to the author's best knowledge. From the perspective of severe economic slowdown, a recession, reduced income, rising unemployment and poverty caused by COVID-19, job insecurity is a crucial variable. Therefore, JI was added as a new dimension to the earlier studies, as an essential variable for study in a COVID-induced environment. Organisational psychologists are concerned about job insecurity, and research has shown that it has a negative impact on an employee's levels of anxiety and depression (Bert et al., 2020; Ganson et al., 2021).

This study supports hypotheses H1a, H2a, H5a and H7a and does not support ideas H3a, H4a and H6a. Coronavirus disease 2019 established a climate of job insecurity, or the risk of resource loss (i.e. employment), causing employees to reduce their resource investment (disengaging from job and investing in e-learning) to retain their existing resources (employability). Therefore job insecurity can moderate the association between BI and its antecedents, for example, perceived usefulness, ease of use, self-efficacy and computer experience. However, job insecurity perceptions cannot moderate the affinity between BI and a few of its antecedents, for example, PEJ, computer anxiety and SN. The positive perception of e-learning adoption may be attributed to either securing a better position in the organisation or strengthening the external labour market (Van Hootegem et al., 2019). The positive perception towards e-learning during job insecurity contradicts the studies by Naswall and De Witte (2003) because of the negative attitude developed by job insecurity. The findings in this study contradict the study outcomes by Fawaz and Samaha (2021) about online learning as a cause of depression and anxiety because of a change in instruction methodology among undergraduate students.

Practical implications

Perhaps the most vital implication of this investigation is highlighting the basic idea of applying e-learning as the best coping strategy in the prevalent COVID-19 scenario. Organisations can use it to alleviate job insecurity among employees to reinforce their external labour market position (Van Hootegem et al., 2019) and fill the skill gap required in the organisation. Therefore top management should not focus on short-term financial gains and invest and allocate sufficient funds to e-learning tools, technology and infrastructure. Whitelaw et al. (2020) mentioned that managers could improve employee engagement with digital technology. Understanding the moderating effect of job insecurity on technology acceptance is critical to experts, educators, top management, policymakers, team managers and HR practitioners.

Contributions to theory

The contributions to theory contributions of the current research are multi-fold. Firstly, the recent study by Abdullah and Ward (2016) recommended replication across different domains, disciplines and settings. Moreover, the current research strengthened the previous analysis (Abdullah et al., 2016) by augmenting the moderation effect of JI, as JI seems to be a crucial parameter in the COVID-19 scenario. Secondly, the current study undertook 'JI' as a moderator variable as Abdullah and Ward (2016) recommended. Thirdly, the study's main findings challenged the negative attitude predicted by job insecurity as predicted by Naswall and De Witte (2003). It also reinforces many of the earlier results established in Middle East and Western cultures (Abdullah et al., 2016) and augments coverage of novel demographic and geographic environments. Moreover, the examination conducted in developed countries may be or may not be appropriate for developing countries like India. For continual revalidation of conceptions in varied job contexts, repetitions of research in sociology are encouraged (Agarwal & Gupta, 2018). Fourthly, the study also justifies the positive perception towards using e-learning in organisations in the COVID-19 scenario. Fifthly, the COR postulations proposed by Hobfoll (1989) was employed to clarify the e-learning utilisation mechanism as a coping strategy to alleviate COVID-related job insecurity.

The COR postulations (Hobfoll, 1989) elucidate how employees save, gather, preserve resources and prevent loss of resources. The authors debated that unfavourable fear and anxiety because of COVID-19 exhaust employees' energy levels, resulting in loss of resources. Therefore employees strive to save their available resources while deciding about their list of activities for execution, including their achievements (Hobfoll, 2001; Hobfoll & Shirom, 2000). It indicates that employees utilise resources like e-learning to regain their lost resources. However, according to COR, such predicted behaviour is contingent on employees' ability to use relevant personal resources to offset resource losses caused by pandemics like COVID-19 (Hobfoll & Shirom, 2000). Though GETAMEL constructs have been the subject of a few investigations in the past (Abdullah et al., 2016), the moderation effect of job insecurity examined in the present study makes the study unique. Employees undergoing COVID-related job insecurity show low perceived employability, which motivates employees to strengthen their position outside the organisation (Van Hootegem et al., 2019); hence they develop a positive perception of e-learning usage. The research adds to the literature on positive attitudes towards e-learning (Elahi et al., 2021; Khan et al., 2020). The current analysis augments the information about the affinity between the variables under consideration and confirms the previously established link.

Shortcomings and future scope of research

The recent work has a few shortcomings, just like any other study. The current investigation employed a limited sample size influencing the accuracy and steadiness of approximations of parameters. Because of the minuscule sample size, as Cohen (1992) suggested. The authors are confident in the validity of their results because the majority of their assumptions were accepted. *The restrictions imposed because of COVID-19 were the main constraints of the researcher. Few employees were not available for participation in the survey because of the severe effect of COVID-19.* The utilisation of self-reported survey data is assumed to have inherent biases. Despite efforts to mitigate common method bias, as advocated by Podsakoff et al. (2003), the possibility of vestiges of common method bias remains. The study comes out with 'new landscapes' for future research in a promising way. Future researchers could generalise results by enhancing sample size and diversity in the sample in various other economies and other industry sectors for broader coverage. Future studies may conduct a comparative survey of employees' perceptions in COVID-19 and non-COVID-19 scenarios. This study explores a new vista to observe the moderation function of job insecurity caused by COVID-19 on the relationship between behavioural intention for e-learning utilisation and its antecedents. As a result, the authors recommend that future research may expand the findings in this study by looking at the other moderator-mediator variables, for example, perceived employability, etc.

Conclusion

To summarise, the data show that in the COVID-19 scenario, job uncertainty substantially modifies employees' positive attitudes regarding e-learning. The current study finds escalation in the overall behavioural intention of employees for e-learning as job insecurity moderates the linkage of BI to most of its antecedents significantly. As e-learning satisfies all COVID-19 protocols, it keeps employees from falling into the traps of negative attitudes because of job insecurity and inculcates positive perceptions. Therefore, it can be concluded that e-learning is a panacea in the COVID-19 scenario.

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Competing interests

The authors declare that they have no financial or personal relationships that may have inappropriately influenced them in writing this article.

Authors' contributions

S.R.N. made a substantial contribution to the conceptualisation and design of the study. S.R.N. collected data from various organisations. P.S. contributed to the final presentation of data. T.S. supervised the data analysis stage and finalised the article. SC contributed to the literature review to meet the reviewer's remarks. SNW elaborated on COR Theory and refined theoretical contributions. RM contributed to the final manuscript writing after considering the reviewer's comments.

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Data availability

Data are available from the corresponding author S.R.N., upon reasonable request.

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