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## Technology & behavioral changes mediation for personnel safety intentions: Crisis in theoretical framework.

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### ABSTRACT

With a theoretical S-O-R (stimulus-organism-response) framework, the study focused on the technology and behavioral changes ensuring personal safety intentions in developed countries. Covid-19 Crisis made the scenario feel the difference in rich people's society or not? Rare research focused on technology-related behavioral changes due to the 20<sup>th</sup> century and a surge in data insights. A random sampling technique was used to analyze data from 580 individuals. At first, P.L.S. (partial least square) analysis proved that leisure, health anxiety-related information flow, and especially new social media trends had substantial effects on technology and behavioral changes. Statistical results, including time series and correlation results, focused more on personnel safety intentions in China. Individual-based historical data proved a huge data use intentions change even until 2022. Hence, the first-ever preliminary research findings will open a new aperture in information management.

### 1. Introduction

Advanced data banquet and technology-related behavioral changes, for personal safety in crisis, especially for government and companies seeking hybrid development, is a future core concern. In recent decades, technology advancements have been improved rapidly and used in different ways in our daily life; communication health improvements such as social distancing, staying home, and wearing mask was positive responses (Mohamed Ridhwan & Hargreaves, 2021). Just because COVID-19 (Coronavirus disease 2019) has confounded tourism in many national economies (Liu et al., 2022). This wide-ranging tendency of technology and behavioral changes could be an opportunity for personal behavioral changes as well as a time to get benefits to increase the adoption of on-line platforms

However, challenges in the health domain have also increased. Earlier, 70% of mortalities were caused by different chronic diseases, as chronic diseases were the primary cause of death worldwide (Yusuf et al., 2020). But new diseases and virus safety protocols have been discovered, such as the coronavirus (COVID-19) outbreak (Yasir et al., 2020). So, personal safety intentions are essential to promote health.

In the 21<sup>st</sup> century, the technology significantly impacts an individual's life, primarily mobile technologies. For example, big data science

provides accuracy and speed for compliance issues (Unhelkar et al., 2022). New technologies deliver enough sustenance according to individual likings (Wongvibulsin et al., 2019) (Spanakis et al., 2016) using algorithms and technological power. Technology changes can stimulate online individuals to change in collective actions about technology use and, as a responsible individual level safety intention. Eventually, these responses can steer a positive change in society or give provisions to individuals and favor the growth of technology adoption behavior and possible motivation for personal safety intentions.

This study focuses on how personal safety intentions are mediated by technology and behavioral changes due to technological advances and facilities. Many factors may contribute to increasing health anxiety of the individuals, such as trends on social media, i.e., daily updates and news may improve personal intentions for safety concerns. It may give motivation to an individual for personal protection. According to Self-determination theory (Deci & Ryan, 2008), it can increase or decrease these motivations. During exceptional circumstances such as pandemics, an individual's leisure time may be influenced by technology. Recently, (Verma et al., 2022) motivated research questions about technology-related behavior because big data and smartphones are changing virtual tourism and user experience. Technology-based apps may stop an individual from going out for a picnic or travel due to the lockdown and limit their time using technology as AI-based advances by 60% (Herath & Mittal, 2022).

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Research data is still limited about behavioral changes due to technology. This study contributes to the crisis positively on technology information acceptance and use by shedding light on the 2022 truth that technology will shape the future and personal safety facts. Social media apps are one of health technologies' primary sources for seeking information (Reveilhac & Blanchard, 2022). Another perspective of the study contribution is identification of behavioral changes for online users about personal safety intentions using user comments, recently text mining proposed by (Kar & Dwivedi, 2020). In current pandemic situation, increasingly plentiful trace data deliver an opportunity for information systems (Berente et al., 2018). Modern research also confirmed the behavioral challenges in consumers and infrastructures of companies (Gandhi & Kar, 2022). Thus, trends and information shared on social media may enhance personal safety intentions. The above literature encouraged us to these research questions

RQ1: Does the crisis bring technology-related behavioral changes?

RQ2: Is there any impact of social media trends and health anxiety on personal safety intentions?

RQ3: How do the technology-related behavioral changes positively impact the personal safety intentions?

The next sections are structured as follows; in Section 2, we provided theoretical background, i.e., the S.O.R model. Section 3 presents the conceptual research model and hypothesis development based on the literature review. The research methodology is presented in Section 4. Data analysis and results are presented in Section 5, including Smart PLS-SEM (software used for analysis). In Section 6, we discussed our results. The conclusion is given in Section 7.

## 2. Theoretical Modeling

### 2.1. S-O-R model

A study of the stimulus-organism-response model enlightens the role of technology and behavioral intentions, with a research gap about personal level safety intentions. S.O.R. has been applied in data science for social media and interactivity (Hewei & Youngsook, 2022), for social media and brand communities (Kamboj et al., 2018) for media richness (Zhao et al., 2020), and health information and intentions in pandemic (Song et al., 2021). And for feelings, as (Sun et al., 2021) mentioned, "pleasant arousal."

Based on the recent above research findings, we extended this model for the crisis and data insights as a flood of information. Because anyone feels the surge in information use in 2022. The theory provides the basics of stimulus, as (Mehrabian and Russell, 1974) mentioned in their preliminary study. That "stimulus" impacts something in the learning or knowledge process, called an "organism," which will result in the final effect of a "Response" scenario. Following them, we used technology and behavior change as an organism, as (Yasir, Hu, Yang, et al., 2022) used the driver's behavioral changes as an organism, an important role, so we took it as a mediator. To know the specific indirect effect on the DV (dependent variable) from IV (independent variable).

The study focuses on the theoretical-based goals in response to "personal safety intentions." As per the author's information, first-ever research study. Notably, the environmental concerns about technology were health anxiety, leisure time, and in China, the "New social media trends; in theoretical extension, we termed them as the stimulating factors (Fig. 1). Compared to S.O.R, another researcher (Irfan et al., 2021) used the theory of planned behavior.

## 3. Conceptual Model and Hypotheses Development

### 3.1. Health anxiety

Health anxiety is described as uncertainty and worries about getting health problems and issues which may lead to increased checking, infor-

mation seeking about health conditions, searching on the Internet about signs and symptoms of sickness, and escaping stimuli related to health (Diagnostic and statistical manual of mental disorders: DSM-5TM 2013). Therefore, social media is the priority for the welfare of the young generation (Sharma et al., 2022). Individuals show different ways of anxiousness about health. For example, health anxiety may make someone less socialite because of disease risk (Mortensen et al., 2010). During the epidemic, traveling got limited due to the threat of covid-19 (Moran, Goh, et al., 2021). Many individuals minimize their casual sex desires due to health anxiety. Many researchers supported this point of less attitude toward physical relationships due to anxiety about getting the disease (Moran, Kerry, et al., 2021). Our research focused on whether health anxiety leads to increased use of technology and behavioral changes, which can enhance their safety intentions. Individuals with health anxiety and worries are more likely to use technology to gather information and connect with physicians' online (Onyeaka et al., 2020).

These notions lead us to the proposition that health anxiety might positively impact the technology and behavioral changes in the individual's life. It means that health anxiety may motivate the individual to seek information, use technology and make changes in their behavior to avoid illness which shows enhancement in their safety intentions. Thus, we hypothesized

H1a: Health anxiety impacts technology and behavioral changes.

H1b: Health anxiety impacts personal safety intentions.

### 3.2. Leisure time

Leisure time shapes the individuals' experience and relationships with positive emotions (e.g., enjoyment, success, and affiliation) to acquire novel knowledge with skills (Folta et al., 2022). Anxiety and loneliness mediate leisure activity and cognitive function (Li et al., 2021).

To evaluate leisure time and individuals' experiences, we acknowledged features such as time-frequency, leisure interest, and digital leisure. Our study uncluttered these factors. In recent crises, technology has changed how individuals spend their leisure time. For example, online adverse effects result in destructive behavior (Behera et al., 2022). For many decades, technology has been a hot issue. But how a pandemic and especially lockdown maximum time to use social media information, we explored time of leisure, interest in digital leisure, and maximum involvement in online leisure activity. In our research, we have examined the correlational relationship between leisure time and technology-related behavioral changes. Lastly, the relationship between leisure time's positive or negative impact on personal safety intentions at the individual levels. So, these two proposed hypotheses are required to be confirmed.

H2a: Leisure time impacts technology and behavioral changes.

H2b: Leisure time impacts personal safety intentions.

### 3.3. New social media trends

Nowadays, people get health information from social media, so social media is becoming a key source of health information (Polansky et al., 2018). As described by (Reveilhac & Blanchard, 2022), social media apps are the most convenient and suitable source for health information. Therefore our study highlights and focuses on health practices done by citizens on social media (Lupton, 2012). People adopt new options as an alternative, e.g., electric bikes (Yasir, Hu, Ahmad, et al., 2022). In this study, we tried to find social media applications' impact on behavioral change and information seeking (Koteyko et al., 2015). For this purpose, people tend to follow social media, i.e., WeChat and Weibo, to get the latest health information. Thus, we hypothesized

H3a: New social media trends impact technology and behavioral changes.

H3b: New social media trends impact the personal safety intentions

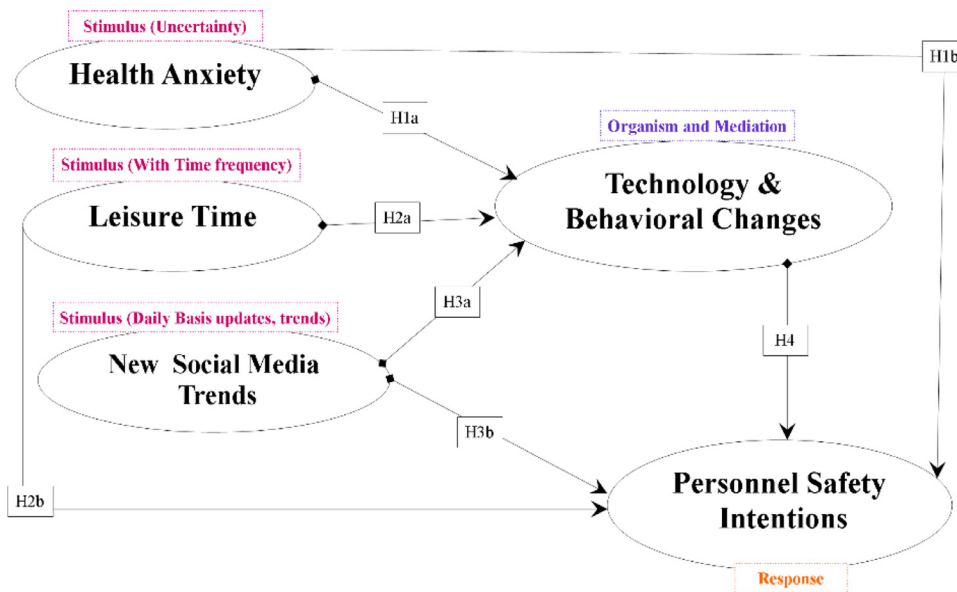


Fig. 1. Conceptual Research Model.

3.4. Mediation: technology and behavioral changes

As described above, health anxiety, leisure time, and social media trends impact personal safety intentions. However, this impact may increase due to technology and behavioral changes. New technologies may motivate individuals to enhance their health condition, improve their lifestyle, and enable people to self-control their health problems (Spanakis et al., 2016), enabling various technologies (Ahsan & Siddique, 2022). For instance, people get information about areas with pandemic cases or acquire knowledge about any risk factor, motivating them to work from home using technology. Technological innovations will help people manage their problems and be involved in a healthy lifestyle in the upcoming decades (Dunton et al., 2009) substantial demand for IT jobs (Koch et al., 2021). Information technology can make health services based on community and personal levels, permitting individuals to increase health knowledge and decrease their health anxiety. It allows them to improve their leisure time in different and safe ways (Schulz et al., 2014) (Büschel et al., 2014), which may lead to obtaining a healthier lifestyle (van Gemert-Pijnen et al., 2011). Above mentioned notions and ideas encourage us to hypothesize that

H4: Technology and behavioral changes impacts personal safety intentions.

H5a: Technology and behavioral changes mediate the relationship between Health anxiety and personal safety intentions.

H5b: Technology and behavioral changes mediate the relationship between leisure time and personal safety intentions.

H5c: Technology and behavioral changes mediate the relationship between new social media trends and personal safety intentions.

4. Research methodology

4.1. Data collection

Data collection and sample information are going through challenging situations in the pandemic; a small amount of e-cash was given to all members to build the premium review. Data were collected from 600 members. Only 580 valid samples were included in the data investigation. We excluded information from 20 individuals who were not filled in correctly. Participants’ demographics are in Table 1.

4.2. Scale development

Fig. 2 presents the survey items adopted and modified from previous research as shown in Table 2.

Table 1 Demographic data.

	Groups	Frequency	Percentage %
Gender	Male	329	56.72%
	Female	251	43.27%
Marital status	Married	168	28.96%
	Unmarried	359	61.89%
	Divorced	53	9.31%
Age	Under 18	48	8.27%
	18-30	301	56.37%
	30-40	142	24.48%
	40-50	51	8.79%
	Above 50	38	6.55%

5. Data analysis and results

The use of smart PLS-SEM (partial least squares structural equation modeling) prominently increased after 2013 in various kinds of research (Scherer, 2005). Mixed-method analysis minimizes the biases that have an impact on research findings

(Patton, 2002), in our research, we also used different approaches. Especially in management research based on conceptual research models with many variables (Joseph F Hair et al., 2012), the use of PLS-SEM has increased. Moreover, the PLS-SEM technique has been largely used in research based on theory and investigation (J. Hair et al., 2017). Besides this, previous studies show that this technique has been extensively used in many branches of management. As research on technology and behavioral changes did not get much attention from scholars about health anxiety, existing literature did not sufficiently explain behavioral changes associated with technology, health anxiety, and trends in social media. Hence, we applied this exciting technique of PLS-SEM in our recent study to check our variables’ direct and indirect effects (mediation) (Joseph F Hair et al., 2012). We checked biasness by finding correlation of variables; the non-correlation was above 0.90, which shows no biases (Wang, 2019). And following (Yasir, Hu, Yang, et al., 2022) suggestion, we also confirmed our HTMT test for correlation business check.

5.1. Word Scrapping

Microsoft Office has “power BI” software to analyze qualitative words, especially trends. So, the big data about discussion or the top trend by the user arguments we analyzed. A similar technique was used by (Adikari et al., 2021) to “detect the public emotions.” (Huang et al.,

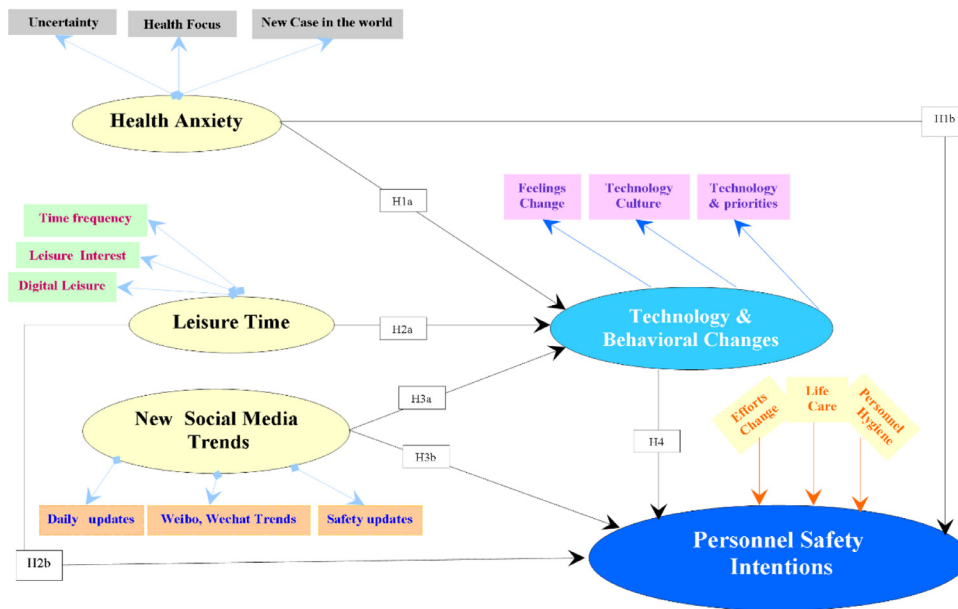


Fig. 2. Conceptual Model with Measurement Items.

Table 2  
Measures of the scale.

Variables	Items	Source
Health Anxiety	HA1: Uncertainty HA2: Health focus HA3: New case in the world	(Verkijika & De Wet, 2019)
Leisure time	LT1: Time-frequency LT2: Leisure interest LT3: Digital Leisure	(Chamarro et al., 2021)
New social media trends	NSMT1: Daily updates NSMT2: WeChat/weibo trends NSMT3: Safety updates	(Mody et al., 2020)
Technology and behavioral changes	TBC1: Feeling the change TBC2: Technology Culture TBC3: Technology and priorities	(Marcus et al., 1992),(ROLLNICK et al., 1992),
Personal safety intentions	PSI1: Efforts change PSI2: Lifecare PSI3: Personal hygiene	(Verkijika & De Wet, 2019)

2022) used this technique for online reviews. Fig. 3 shows the results of the primary data.

### 5.2. Measurement model assessment

We tested composite reliability (CR) and discriminant validity to check measurement model assessment (J. Henseler et al., 2015). To measure discriminant validity, we compared variables and calculated the square root of AVE (average variance extracted) (J. Henseler, Ringle, et al., 2016). Factor loading values > 0.70 (Joe F Hair et al., 2011). Values of average variance extracted (AVE) must be higher than 0.5 (Chin, 2010). Similarly, composite reliability (CR) should be greater than 0.7 (J. Henseler, Ringle, et al., 2016), and rho should be higher than 0.7 (J. Henseler, Hubona, et al., 2016).

All these values for measurement model assessment are given in table 3, including values of outer loading, alpha, Rho, CR, and AVE. Table 4 shows the discriminant validity.

### 5.3. Structural model assessment

Bootstrapping technique with 4000 resamples was used to measure the imaginary relationship between variables of our conceptual research model by measuring t-values and confidence intervals. A previous study (Streukens & Leroi-Werelds, 2016) shows that bootstrapping resamples can be used from 500 to 5000. bootstrapping is used to check incon-

sistency and irregularity in data to find out statistic inconsistency, and it is a non-parametric method of resampling to check approximate accurateness. However, (Efron & Tibshirani, 1994) prescribed using at least 1000 resamples or more in bootstrapping. Mediation can only be found if the direct effect among variables is significant. Immediate effects among variables of our study are shown in Fig. 4. Direct effect and t-values, along with  $f^2$  are given in table 5. Analysis shows the significant direct effect among variables. Especially new social media trends showed a strong direct effect on personal safety intentions. As presented in Fig. 4 and Table 5, the relationships among variables were supported (Leguina, 2015) except for one relationship between leisure time with technology and behavioral changes for the direct relationship hypothesis.

We measured the confidence interval to find out the path coefficient. They were supported because zero values were not included in the confidence interval (J. Henseler, Ringle, et al., 2016). Model fit criteria in used in PLS-SEM path modeling in standardized root mean square residual (SRMR). We measured the fitness of the model by calculating different standard values such as the normed fit index (NFI), the non-normed fit index (NNFI), root mean square error of approximation (RMSEA), and SRMR values  $\geq 0.95$  in NFI, NNFI, and CFI specify the most acceptable fit. RMSEA and SRMR significantly adjusted with values < 0.06 (Byrne, 2013a). The cutoff value of SRMR and RMSEA with 0.08 and 0.06 are considered best for perfect model fit. According to some authors, if SRMR is zero, it shows an ideal fit; however, according to





**Table 4**  
Discriminant Validity.

	HA	LT	NSMT	PSI	TBC
HA	<b>0.822</b>				
LT	0.804	<b>0.785</b>			
NSMT	0.771	0.749	<b>0.789</b>		
PSI	0.708	0.700	0.735	<b>0.939</b>	
TBC	0.701	0.678	0.783	0.691	<b>0.895</b>

Note: Bold values shows the square root of AVE. It must be higher than the values in its column.

(Byrne, 2013b), if the value of SRMR is less than 0.05, it also indicates a satisfactory model fit.

We checked our research model's predictive strength by checking the coefficient of determination  $R^2$ . Significances of the independent variables on dependent variables were also found.  $R^2$  is a very significant and vital factor for this assessment.  $R^2$  can also be used to check the prediction of future outcomes or also can be used to investigate hypotheses based on given information. Thus,  $R^2$  delivers measurement outcomes and explains the outcomes' sensibleness (HooperD & Mullen, 2008). Investigators can also use smart PLS-SEM to determine the predictive power of their conceptual research model out of sample. (Joseph F Hair et al., 2012). The value of  $R^2$  can differ from 0 to 1; hence, a higher value indicates the best explanatory power. If the value of  $R^2$  is 0.75, it shows significant descriptive power, similarly, 0.50 and 0.25 for moderate and weak, respectively (Rigdon, 2012). However, compared to CB-SEM, the new technique of PLS-SEM is less dependent on model fit (Sarstedt et al., 2016). As suggested by (Joseph F Hair et al., 2012), the cutoff value of RMSEA  $\leq 0.08$  using the adjustment in  $R^2$ , effect size ( $f^2$ ) finally shows that the effect size of the dependent variable on the independent variable was acceptable.

5.4. Effect size

If independent variables affect dependent variables, it can be a strong, mediate, or weak effect. We used  $f^2$  to check this effect size. We used the blindfolding technique to measure the power and strength of our conceptual model. Cohen's  $f^2$  is standard to check whether the effect level is strong or weak. Moreover, it can calculate the local effect size, i.e., comparing multivariate model regression with one variable (Selya et al., 2012).

$Q^2$  shows the predictive relevance; if the value of  $Q^2$  is higher than 0, it shows a good prediction of the research model (Cohen, 1962). In this study, we tried to focus on in-sample prediction; significant predictive  $Q^2$  is also considered a standard for calculating predictive relevance rather than only focusing on  $R^2$  (Cohen, 1962). Final evaluation and assessment include  $R^2$ ,  $Q^2$ , and  $f^2$ , which are significant conclusive factors. Except for this assessment, the inner model should also be assessed to find co-linearity problems. Outcomes of the internal model are considered biased if variables are interconnected (Aguinis et al., 2016).  $R^2$  measures the predictive accurateness. It also defines the significance of

**Table 5**  
Structural model assessment.

	Relation	Direct Effect	t-value	Decision	$f^2$	2.5%	97.5%
H1a	HA→TBC	0.173***	2.782	Accepted	0.024	0.038	0.301
H1b	HA→PSI	0.187**	2.391	Accepted	0.026	0.035	0.340
H2a	LT→TBC	0.119*	1.720	N Supported	0.012	-0.015	0.253
H2b	LT→PSI	0.202***	3.127	Accepted	0.033	0.075	0.327
H3a	NSMT→TBC	0.560***	10.757	Accepted	0.312	0.458	0.660
H3b	NSMT→PSI	0.281***	3.805	Accepted	0.057	0.128	0.433
H4	TBC→PSI	0.202***	3.544	Accepted	0.039	0.065	0.312

Note: significance level (p values) \*\*\* means  $p < 0.005$  = significant, \*\* means  $p < 0.05$  = moderate significant, \* means  $p < 0.5$  = insignificant.

**Table 6**  
Effect Size and predictive relevance.

Dependent Variable	$Q^2$	$R^2$	Independent Variable	$f^2$
TBC	0.507	0.641	HA	0.024
			LT	0.012
			NSMT	0.312
PSI	0.540	0.621	HA	0.026
			LT	0.033
			NSMT	0.057

Note: HA, LT, NSMT, TBC, and PSI denote health anxiety, leisure time, new social media trends, technology and behavioral changes, and personal safety intentions, respectively.

independent variables on dependent variables. Its values can differ from 0 to 1. Table 6 shows the values of  $Q^2$ ,  $R^2$ , and  $f^2$ .

For each path model, we measured  $f^2$  to measure the effect size. After removing a variable from the research model, we measured Cohen's  $f^2$  without changing  $R^2$ . There are two path models to measure  $f^2$  in PLS-SEM. Standard values of  $f^2$  can be used to find the effect size of the removed variable on the dependent variable. The standard values for  $f^2$  are 0.02, 0.15, and 0.35 weak, moderate, and strong effect sizes, respectively (Aguinis et al., 2016). The above discussion supports our research variables and mediations.

5.5. Mediation test

For the mediation test about the technology and behavioral changes, we applied a popular new technique recommended by (Nitzl et al., 2017). The below equation shows the specific indirect effect and the total effect of independent variables on the dependent variables. Moreover, we calculated the magnitude or level of mediating effect (F. Hair Jr et al., 2014). VAF is used for the mediation test; it means variance accounted for. It shows the mediation in percentage.

Magnitude, mediation strength (VAF)=specific indirect effect/ total effect

- H5a=Health anxiety → Technology and behavioral changes →personal safety intentions/Total effect [0.105/0.286=36.7133%]
- H5b=Leisure time → Technology and behavioral changes →personal safety intentions/Total effect [0.021/0.227=9.2511%]
- H5c=New social media trends→Technology and behavioral changes→personal safety intentions/Total effect [0.046/0.34=13.5294%]

At the advanced level, (Mehmood et al., 2018) and (Yasir et al., 2020) used this technique for multiple mediation effects. But we used only a single mediation effect.

6. Discussion

Data insights and technology-related behavioral changes bring innovative opportunities with digital-based planning for companies' businesses, government management techniques, and individual-level considerations. Behavioral changes need an optimal understanding from the

users' point of view. This research examines the encouraging factors that how crisis shapes personal behavioral intentions within mirrors behavioral changes.

### 6.1. Contributions to literature

S.O.R. theory extension based, triangle method technique with novelty-based research gap performed the analytics analyzed on the primary and secondary datasets prepared in the lenses of statistical approaches about quantitative data, e.g., P.L.S. based relationships between the proposed business-related opportunity for the government and companies due to crisis scenario. Compared to the S.O.R. model technology accepted model is used in Saudi Arabia (Al-Mamary, 2022). Qualitative analysis has been trailed in the sense of secondary data from S.N.S. (social networking service) of Weibo and friends circle-based posts posted by the users who participated in the pilot study analysis. The third analysis, based on big data, and word scrapping, proved some interesting, meaningful directions for the companies and government to maximize control and implement new targets.

The findings confirmed that new social media trends significantly positively influenced the technology and behavioral changes ( $\beta=0.560$ ,  $p<0.5$ ), parallel to (Neogi et al., 2021) social media exponential rise. Parallely, the second significant impact is new social media trends on personal safety intentions ( $\beta=0.281$ ,  $p<0.5$ ). The third significant impact was leisure time on personal safety intention by  $\beta=0.202$ ,  $p<0.5$ . Surprisingly and interestingly, technology and behavioral changes impacted with  $\beta=0.202$  on personal safety intentions.

A solution for knowledge and social self-awareness for leaders (Tiwari & Raman, 2022). While interacting with behavioral changes related to technology has a much more significant relationship with health anxiety-specific indirect effect on personal safety intentions with 36.7133% VAF. Like, during the crisis, a flood of online users has discussed coping with the risk associated with personal safety intentions under the lockdown crisis in the world. Recent researchers suggested the difference in technology adoption based on health-related threats and coping scenarios for a better society, e.g., no cases in their relevant community in China and developed countries. Similarly, with behavioral novelty about technology use, findings suggest that health anxiety promotes the behavior about technology and safety intentions. So, health anxiety, leisure time, and social media trends in 2022 about new cases or the safety-related trends mitigated the threats due to increased personal safety intentions.

Additionally, the mediation mechanism of behavioral changes about the technology role, especially in a crisis management perspective, in the cumulative relationship, for example, with specific indirect effect with VAF. technique, calculation as a specific indirect effect divided by total effect as health anxiety to technology and behavioral changes to personal safety intention is a specific indirect effect ( $=0.105$ ), and the total effect of these variables is 0.286. Accordingly, specific indirect effect/total effect ( $0.105/0.286=36.7133\%$ ) of these relationships. A strong and very valid due to significant p values ( $p=0.005$ ).

Nevertheless, study findings of the relationship of leisure time to technology and behavioral changes on the personal safety intention in a specific indirect effect are ( $\beta=0.021$ , specific indirect effect) with total effect  $\beta=0.227$  is not supported for V.A.F. values, e.g. (VAF=9.2511% for H5b and 13.5294% for H5c).

### 6.2. Practical implications

This study encourages companies to use this opportunity based on the framework of a behavioral change that can involve the maximum customer to have more clicks and customer engagement in the crisis. For example, (Kumar et al., 2021) social media analysis provides mitigation for risk management. Further practical and managerial implications are; (i) Physical touring companies must open the digital version to improve the number of customers and their ease of use. (ii) Companies should

open digital shops in crisis and continue for weekends etc. (iii) Leisure time increase brings behavior change, so companies should open more marketing ads in this time, so buy online and get home delivery to make the customer convenient. (iv) Results proved that technology and behavioral changes bring personal changes in hygienic habits, or it means new adoption of telemedicine will be maximum if pharmacies and government focus on safety-related products. (v) If the new cases are increasing, the government should not only focus on information flow but to change the behavior, especially technology behavior, for example, push companies to open a discount on online purchases, etc., and home delivery with tax exemption. (vi) For individuals at the village level or in less developed cities, the government should encourage them to connect leisure time with behavioral changes and safety intentions. (vii) leisure time intensifies personal safety intentions; organizations' management should focus on personal safety intentions and a hygienic environment during and after pandemic conditions using technologies to improve behavioral changes. (viii) New social media trends bring technology and behavioral changes; companies should use social media platforms to encourage customers towards their products and technology, especially hot trends. (ix) New customers can be attracted by activities in shopping malls by promoting online shopping applications and encouraged to use technology to get more benefits.

### 6.3. Limitations and future research

Together, study insights advance technology and information literature, companies, and planning division understandings for not only in Covid-19 crisis but sustainable future technology-based behavioral changes. For example, COVID-19 impacts are diffused to related economic sectors (M. Henseler et al., 2022). More specifically, how social and physical distancing-based leisure changes, health anxiety, e.g., behavioral changes as a solution (Yasir, Hu, Yang, et al., 2022), and new trends with personal safety intentions are shaping future technology-based opportunities.

## 7. Conclusion

The study findings emphasize the importance of strongly mediating technology and behavioral changes with data use surge in crisis. The proposed theoretical model with S-O-R provides evidence with the stimulus of new media trends, leisure with time, and digital leisure interests due to Covid-19 and health anxiety incentives to maximum use of technology. For this, the following (Hanaysha, 2022) perceived relevance, and interactivity effects purchase decisions, could be used to understand digital tourism and online users. Moreover, this research confirmed that technology-related personal use and feelings induced by crisis-related health anxiety and a surge in social media use. This research tackled the gap between users' change in technology use behavior that brings knowledge for individual-level personnel safety intentions. The reason why users gain crisis-related behavior concerning digital leisure, media trends, and health anxiety stimulus since uncertainty-related discomfort decreases with exposure (Arend, 2022).

Overall, the study contributes to the crisis positively on technology information acceptance and use by shedding light on the 2022 truth that technology will shape the future and personal safety facts. A momentous query that emerges with research findings is the possibility of marketing, business, safety, and tourism trends connected with technology-related behavioral changes based on the initial pandemic stimulus. In the past, (Dwibedy, 2022) confirms that informal competition affects innovation in transitioning.

### Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.



## CRedit authorship contribution statement

**Saba Ali Nasir:** Conceptualization, Writing – original draft, Methodology. **Ali Ausaf:** Conceptualization, Writing – original draft, Methodology, Writing – review & editing. **Zuguang Shi:** Investigation, Data curation, Writing – review & editing. **Ziting He:** Investigation, Data curation. **Ammar Yasir:** Software, Validation, Formal analysis, Writing – review & editing, Supervision, Funding acquisition.

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