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Personal elearning management in the context of COVID-19 among university students in Saudi Arabia

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Badr A. Alharbi[1], Usama M. Ibrahem[1,2], Mahmoud A. Moussa [2], Mona A. Alrashidy [1], Shimaa M. Abdelwahab[3], Bahgat A. Radi[1] and hanan M. Diab[1]*

University of Ha'il – Kingdom of Saudi Arabia [1], Suez Canal University, Egypt [2], Mansoura University, Egypt[3]

***For Correspondence:** Email: *u.abdelsalam@uoh.edu.sa*; Phone: +966567578899

Abstract

The study aimed to study the performance expectation in future tasks based on personal learning management during the Corona epidemic. A random sample of 871 students from the University of Hail was selected. The study samples were from humanities, engineering, and medical colleges. The study was based on a cross-sectional study design. The study prepared a measure of future expectation of performance on the tasks. The scale is 28 items. Factor analysis was used to verify the validity of the scale, and the scale achieved acceptable indicators of good fit. The scale achieved acceptable stability using Cronbach's alpha coefficient for emotional factor 0.57, cognitive factor 0.94, and behavioral factor 0.90. The results revealed that there are differences in the future expectation on performance because of gender and type of college. The results revealed that there are positive correlations between future expectation of cognitive and emotional performance, as well as a positive relationship between emotional and behavioral performance. There was also a negative relationship between behavioral and cognitive performance. *(Afr J Reprod Health 2024; 28 [4]: 111-126).*

Keywords: Personal e-Learning Environment (PLE); Distance Learning (DL); Future Tasks; Expectation; Performance

Résumé

L'étude visait à étudier les attentes de performance dans les tâches futures basées sur la gestion de l'apprentissage personnel pendant l'épidémie de Corona. Un échantillon aléatoire de 871 étudiants de l'Université de Hail a été sélectionné. Les échantillons de l'étude provenaient de facultés de sciences humaines, d'ingénierie et de médecine. L'étude était basée sur une conception d'étude transversale. L'étude a préparé une mesure des attentes futures en matière de performance pour les tâches. L'échelle est de 28 items. L'analyse factorielle a été utilisée pour vérifier la validité de l'échelle, et celle-ci a atteint des indicateurs acceptables de bon ajustement. L'échelle a atteint une stabilité acceptable en utilisant le coefficient alpha de Cronbach pour le facteur émotionnel de 0,57, le facteur cognitif de 0,94 et le facteur comportemental de 0,90. Les résultats ont révélé qu'il existe des différences dans les attentes futures en matière de performance en raison du sexe et du type d'université. Les résultats ont révélé qu'il existe des corrélations positives entre les attentes futures en matière de performances cognitives et émotionnelles, ainsi qu'une relation positive entre les performances émotionnelles et comportementales. Il existe également une relation négative entre les performances comportementales et cognitives. *(Afr J Reprod Health 2024; 28 [4]: 111-126).*

Mots-clés: Environnement personnel d'apprentissage en ligne (PLE); Enseignement à distance (DL); Tâches futures ; Attente; Performance

Introduction

The global COVID-19 outbreak has caused an anxious situation in every part of society and forced many countries to implement distance education programs without even knowing the fundamental components involved in the processes and the consequences of their decisions. COVID-19 has been a trigger for educational institutions worldwide to pursue creative approaches in a relatively short notice.

The epidemic drove many on-campus practitioners to use a different course delivery method than F2F. Most institutions now use Blackboard, Microsoft Teams, Zoom, or other online services. However, researchers disagree on the integrity of DL efforts. Some organizations reported a smooth deployment, while others felt unprepared. Universities offered online and offline synchronous and asynchronous course delivery tutorials for struggling academics. They also deployed support staff to departments to assist academics. At this stage, academics had only technical support, which was insufficient to ensure instructional quality[1,2]. This has revolutionized learning techniques and encouraged creative and personal learning. Personalized learning is a dynamic knowledge delivery method[3]. PLE is a living experience that lets students reflect, think, and act. Group talks promote cognitive flexibility in dealing with cognitive schemas[4]. Although there is no universal definition of this phrase, it refers to both the web-based technologies used to aggregate and produce material on the web and the personal experiences and processes that contribute to learning. A learner controls the tools and content of his/her PLE, which may expand and alter throughout his/her life.

PLE provides possibilities to create an effective learning experience, making the learner and the teacher more flexible in the processes of communication, interaction and information sharing, so that their perceptions expand in the PLE. PLE enables the learner to manage their own learning activities and meet their study needs[4].

Learning is often based on creating independent learning environments for the learner by the teacher or specialists, in order to change the concepts of support and self-regulation for the learner[5], The management of the PLE may suffer from some limitations, including the difficulties of group communication in non-interactive times, its suitability for cognitive-based learning, communication difficulties, and the focus on joint learning more than individual[5, 6]. These challenges do not exist in the e-learning environment.

Global events can spur quick innovation, as seen with e-commerce after SARS. This may not apply to e-learning post-COVID-19, but it is one of the few sectors where investment has not dried up. This pandemic has shown the necessity of knowledge sharing across borders, companies, and society. We must fully study online learning technology if it can help[7]. Unplanned deployments, lack of standards, professors' lack of experience in distant course delivery, increased workload, and different university apps produced uncertainty.

The problem

From the experience of the research team during and after the Corona pandemic, it was noted that there are many differences in dealing with the tasks and study assignments by the learners, especially by transforming the form of learning from F2F to distance learning and relying on the personal skills of learners in managing their learning and overcoming the problems they face. The management of PLE negatively and positively affected the performance of the tasks assigned to the learners; so the research team directed the review and analysis of previous studies, where they found: Every school has switched to online learning due to the COVID19 pandemic, even though nobody was ready. Bernard *et al*. (2014)[8]; Ryan *et al*.[9]; Lockman and Schirmer[10] found that online learning improves course completion, student satisfaction, and motivation to learn more. Online learners' motivation, contentment, skill development, and interaction differ greatly from F2F learners.

The results indicated that the implementations suffered from infrastructural and psychological issues. In terms of infrastructure, the LMS's offered by the universities were not sufficient to conduct classes. Besides, due to the inequality of opportunities, the students could not participate in the activities as desired[1],[11]. Also, previous failure experiences and lack of motivation due to exposure to failure experiences make attention monitoring exaggerated to the extent that anticipating future performance is negatively large[12,13].

Almost, all universities tried to coordinate the characteristics of online learning and the actual needs of students, preventing normal classroom teaching methods, duration, and teaching arrangements from being copied[11,14].

A series of interviews were also conducted with learners about the impact of PLE management on their performance of tasks. The interviews concluded that the management of PLE from a distance had varying effects on the performance of duties and tasks, and some indicated that it changed their way of dealing with tasks, others indicated that the environment PLE was frustrating at first but they got used to it. Also, all confirmed that the Corona pandemic had an impact on learning methods and that they were not ready to shift from F2F learning to managing PLE from a distance.

The lack of effectiveness of the traditional “one size fits all” approach is driving the use of big data analytics, artificial intelligence and remote PLE, which may enable the creation of personalized learning experiences, and this in turn will help to solve some of these challenges. There is also a need to develop students' ability to anticipate the accomplishment of future tasks in their learning.

Study question

1. What is the impact of Personal Learning Environment management during Corona epidemic on the expectation of performance in future tasks?
2. Is the future expectation structure being validate in Saudi Arabia society?
3. Does the cognitive future expectation subscale associate with the emotional and behavioral future expectation in the future tasks during personal learning environment?

Theoretical framework

As in any major crisis situation, COVID-19 has generated not only significant risks, discrimination or costs, but also unanticipated opportunities, substantial human and technological progress platforms, including in the field of Education.

Distance learning (DL):

Defined DL as “improved capabilities in knowledge and/or behaviors as a result of mediated experiences that are constrained by time and/or distance such that the learner does not share the same situation with what is being learned”[15]. DL contributed immensely to the use of ICT for educational purposes[16]. Over the past two decades, distance learning has become pervasive and reliant on ICT.

DL encourages student-centered learning and self-learning. It offers a lot of opportunities to tertiary institutions[15;17], the effectiveness of DL depends on how the courses are designed and how students supported. All the online activities have to be designed in such a way that they support the student in grasping the course content. United Nations Educational, Scientific and Cultural Organization report analyzing potentials and limitations of major distance learning models[20] as in Table 1.

School’s Out, But Class’s on:

“Class’s on” finished all those who depend on determination and inertia in education[18,19]. Commonly, the instructional environment alters, transferring educational activities to offline mode. Online cloud instruction is replacing F2F teacher instruction. Thus, classroom learning becomes autonomous study outside of school. Although school outside learning reinforced the classroom function as an assistant in transferring traditional instruction situations, it is an innovative technique that permits distance learning and teaching.

While highlighting the importance of F2F learning for intra-person and physical interaction, some research shows that the absence of the F2F environment had condensed the interaction level among students and their instructor[14]. Availability of technology is a necessary but not sufficient condition for effective remote learning: DL has been key to keep learning despite the school lockdown, opening new opportunities for suppling education at a scale[21]. However, the impact of technology on education remains a challenge.

Observation from learning systems during COVID-19

Speaking about the impact of COVID-19 and the future of Education, there are opinions of some experts according to which the integration of information technology in Education will accelerate in the future and that the online learning will eventually become an integrated component of school education[7,21]. This base on the following

Table 1: Matrix analyzing potentials and limitations of major distance learning models

Key elements of teaching and learning practices	Categories of distance learning	Online			TV-based		Radio-based		Print-based
Main media and technology tools	Sub-categories of distance learning	Platform-based online learning	Teacher-directed live streaming lessons	Video-based flipped learning	Digital TV	Analogue TV	Interactive Radio	One-way Radio	Textbooks and print material packages
Formats of content	Supporting videos	*	*	*	*	*			
	Supporting multimedia demonstration	*	*	*	*				
	Supporting audio	*	*	*	*	*	*	*	
	Supporting text	*	*	*					*
Devices to access content	Computers (desktop, laptops, or tablets)	*	*	*	*				
	Smartphones	*	*	*			*	*	
	Feature phones								
	Other digital devices, e.g. Kindle	*	*	*					
	TV			*	*	*			
	Radio	*	*	*			*	*	
	Paper		*						*
Management of curricular calendars	Adaptive learning calendars based on different learners and their paces of learning	*		*					
	Online learning calendars accessible anytime and anywhere	*		*					
	Fixed calendar or programs		*		*	*	*	*	*

observation as the ETF's analysis conclusions regarding the current and post-pandemic developments:

- Some positive results were observed in education, respectively benefits of acceleration of the training of parents, teachers, and students

- from all ages, and the other hand the good production of new pedagogical and instruction, educational tools, and methods[22].
- New cooperation and partnerships with the private sector led to many distinguished results, such as providing good academic content, finding new solutions to educational problems, providing equipment, building electronic platforms, finding better learning management to link learning with the labor market[20,21].
- Innovative solutions modify classical learning formulas by experimenting with technological formulas such as practical activity, apprenticeships. Enable those in administrative positions to modify the reactions and habits of mind to go beyond the classic model in management, and the topics of the traditional learning process[18].

According to this perspective, an obvious question became relevant: will the current pandemic be the trigger for transformation?

Personal learning environment (PLE):

A system, application, or suite of applications that assists learners in taking control of and managing their learning. It represents an alternative approach to the Learning Management System (LMS), which by contrast adopts an institution-centric or course-centric view of learning. Key PLE concepts include the blending of formal and informal learning, participation in social networks that transcend institutional boundaries, as well as the use of a range of networking protocols (RSS, peer-to-peer [P2P], Web services) to connect systems, resources, and users within a personally managed space[23,24].

Fiedler and Väljataga[25] see it as a cyber-learning paradigm, which is a type of learning that relies on a network technology to connect learners, resources, and communities within and outside their learning context to support learning enabling sharing of learning experiences and receiving feedback from others. It thus promotes creative learning styles, a type of experiential learning that creates a dynamic process of presenting knowledge through practice, experience, observation, and conceptualization[4].

Characteristics of a PLE:

A PLE provides the learner with the management of learning resources to enhance cognition, manage social interactions, and stimulate social and educational integration. PLE is a fertile environment for implementing self-regulated learning[26]. The PLE enables the learner to adapt and personalize the learning environment, tools, interfaces, and personalization[25]. It is integrated with problem-based learning as it develops skills in research, development, criticism, justification, implementation, and evaluation[23].

PLE provides a live experience that enables the learner to reflect, think about, and act upon, through reinforcement and group discussions[4], and the learner continues to receive feedback and task-performance feedback from peers or the teacher, which has an effective impact on the Self-shaping learning concept[26]. It enables the learner to acquire the ability to critically think, change and modify cognitive structures in deep levels of cognitive processing in an electronic learning environment[4]. Also, it enhances the rich academic experience and achieves a competitive advantage.

PLE has several features: (a) Tangible experiences; (b) Reflective Observation; (c) Abstract Conceptualization; and (d) Active and Independent Experimentation[23,26-28].

The impact of managing a PLE on future performance:

Managing PLE improves learning processes by applying research and knowledge navigation; It helps with social development, adapting knowledge into innovation, enhancing innovation, and increasing competitiveness[6, 29]. It is also characterized by reliance on the learning space, where the diversity of stimuli and the ability to access learning resources, and the provision of a flexible knowledge store; Memory enables immediate processing by thinking from many angles and in innovative ways[3]. It also engages the learner in learning strategies with deep understanding and demonstrates enhanced conceptual learning, creativity, cognitive flexibility, and enhanced self-esteem[30].

The PEL enables the learner to learn by doing and building knowledge, where the motivation for work organization, external organization, which activates the positive social comparison processes that grow among learners in the light of the e-learning environment[6]. It also enables the learner to think forward and to be able to imagine possible upcoming scenarios and test them beforehand. Where thinking is the first stage of future memory[31].

Educational tasks and future performance:

According to the emphatic value theory, achievement emotions can be derived from two components[32]:

- Perceived control: represents the learner's belief in external and personal factors such as intellectual competencies and educational experience, which affect his performance in completing educational tasks.
- Task value: represents the importance that the learner perceives to be related to educational activities and the results of his success or failure in them. The frequency and intensity of the task and the nature of its content is an indicator of the extent of success in performing future tasks.

Momentary emotions result to a large extent from the similarity between previous tasks, and interpretations of negative situations, which may reduce ability[28]. or positive emotions that increase the ability to anticipate the completion of future tasks[33].

Academic performance predictive models

Various prediction models can be employed to forecast academic achievement by considering the management of personal learning environments. These models encompass[34]:

- Machine learning techniques, including decision trees, random forests, and neural networks, can scrutinize extensive datasets of learner PLE data and generate prognostications regarding academic achievement.
- Regression methods, such as linear regression and logistic regression, are commonly employed in academic research to examine the association between parameters related to PLE management and academic achievement[35].
- Time series analysis is a statistical method that can be employed to represent the pattern and recurring patterns of a student's academic achievement over a period of time[36].

These prognostic models can be utilized to detect students who are susceptible to subpar academic achievement and offer focused interventions and assistance to facilitate their enhancement.

Technical literature on PLE management and learning outcomes is abundant. Our article may differ from comparable ones in various ways:
Consider Future Task Performance: Much research has examined the association between PLE management and learning outcomes, but our article focuses on predicting future task performance. In today's fast-changing workplace, transferring learning across contexts and domains is crucial.

- Focus on Personality: Our post may also differ from others by emphasizing personal PLE management considerations. PLE tools and resources have been the focus of previous investigations. We consider motivation, self-regulation, and metacognition in our holistic approach.
- Methodology: Our methodological approach may also distinguish our article from others. Machine learning algorithms can be used to examine PLE management data and forecast task performance. Traditional regression analysis may not make as accurate or nuanced predictions.
- Useful Information: Finally, our article may differ from others in its practical implications for educators and students. Our article can help educators create more effective learning environments that let students apply their knowledge and abilities to real-world situations by forecasting future task performance based on PLE management. The lessons from this post

can also help learners manage their PLEs and perform better in future activities.

Methods

The design of cross-sectional studies was used to investigate the impact of the use of PEL through the continuation of the Corona pandemic on the expectation of performance on future tasks of the university student.

Participants

The study consisted of 871 students from the UOH. The sample was chosen at a simple random. Students' consent to the application has been taken. The participants in the study knew the objectives of the research in advance. The sample was divided in terms of gender into 183 (21%) males and 688 (79%) females. The sample was divided in light of the faculties variable into 141 (16.7%) health faculties, 494 (56.7%) engineering faculties, and 236 (27.1%) humanities faculties.

Data collection and ethical consideration

Online data collection was conducted for the first Semester in October 2021. The online, distance and flexible learning methods were implemented in the first semester of the academic year 2021-2022 to mitigate the spread of coronavirus. Ethical considerations in conducting academic research were applied. Before proceeding to the actual survey, the purpose of this study was clearly explained.

2.4. *Procedure*:

The study group variable was controlled, as it was noted that 93.6% of the participants were in the first academic level, and therefore other study levels were excluded. IBM SPSS 21 and LISREL v8.51 were used in conducting the statistical analysis. Standardized scores were evaluated in emotional performance, as its scores contained positive and negative outliers. The Listwise method is used to treat the missing data. The differences between genders and colleges in cognitive, emotional, and behavioral performance were achieved using the Multiple Multivariate Analysis of Variance (MMANOVA). The association between students' expected performance components was computed using the Pearson correlation coefficients. Given the discrepancy between the sample size of males and females and its significance in the results of the analysis of variance, the effect of gender and faculties variables was isolated using the partial correlation coefficient. Confirmatory factor analysis was used to verify the factorial structure of the university student's future performance measure.

Future expectation scale

The scale aims to identify the learner's perception of his future expectations (cognitive, emotional, behavioral). The scale was prepared after reviewing previous studies García-Garnica *et al.*[38], Dai, *et al.*,[39], Kristoffersen[40].

The initial image of the scale consisted of 38 items in three dimensions. The emotional dimension has 13 items (1-13). And after predicting cognitive performance was 12 items (14-25). Finally, the behavioral performance consisted of 13 items (26-38). The overall items were positive. The five-point Likert scale (5 = always, 1 = never) was used to perform item responses.

Confirmatory factor analysis was used to verify the three-factor model. The results revealed that the model had accepted fit according to the indicators, as NNFI = .91, SRMR = .011, GFI = .92, AGFI = .91, RMSEA = .050, X2 = 60.96 (P=.000), while it was a bad fit in X2 indicator due to the sensitivity of this indicator for the sample size. The item factor loadings were as in Table 2.

Overall items were significant in their dimensions. The item factor loadings of emotional performance ranged between 0.42 to 0.68, while cognitive performance factor loadings ranged between 0.54 to 0.85. The behavioral dimension loadings ranged from 0.21 to 0.80. The internal consistency method was used using Cronbach's alpha coefficient and its value was 0.85. The alpha coefficient of an emotional factor was 0.57, cognitive performance was 0.943, and behavioral was 0.902.

Table 2: The factor loadings of the future expectation model

Factors	N	Factor loading	Std deviation	t-value
Emotional performance expectations	1	.60	.010	58.76
	2	.52	.010	51.45
	3	.42	.009	42.94
	4	.68	.010	67.15
	5	.66	.010	65.41
	6	.63	.010	62.53
	7	.60	.010	59.12
	8	.54	.010	53.52
	9	.58	.010	56.74
	10	.52	.010	52.06
	11	.64	.010	61.78
	12	.55	.010	54.48
	13	.68	.010	66.52
Cognitive performance expectations	14	.79	.011	74.69
	15	.70	.011	74.85
	16	.82	.011	76.76
	17	.75	.011	70.78
	18	.80	.011	75.12
	19	.72	.011	68.62
	20	.78	.011	73.99
	21	.63	.010	60.87
	22	.80	.011	75.24
	23	.84	.011	78.60
	24	.85	.011	79.14
	25	.54	.010	52.31
Behavioral performance expectations	26	.55	.011	49.67
	27	.77	.011	69.14
	28	.80	.011	72.31
	29	.61	.011	55.70
	30	.77	.011	69.68
	31	.21	.011	19.32
	32	.69	.011	62.65
	33	.67	.011	60.53
	34	.78	.011	70.16
	35	.80	.011	72.14
	36	.62	.011	57.18
	37	.80	.011	71.67
	38	.78	.011	69.93

Results

Limitations

The sample size will be a limitation to generalizing the results. Students' disclosure of their future expectations may be exaggerated. Students' expectations are subject to social approval, and these expectations may be incorrect due to the cognitive distortion caused by the epidemic continues and may be due to the discussion and support scenarios that the learner obtains from his peers, upon which he builds his learning later. Personal learning scenarios may vary with self-regulation and co-regulation in a student's interactions with peers in the learning environment.

Descriptive statistics

Descriptive statistics were computed. Table 3 displays the values of the indicators as follows:
It was clear that the data of emotional, cognitive, and behavioral performance are normal. This was confirmed by the Kolmogorov Smirnov test for estimating the normality. The emotional component was normality (K=.975, df=871, p=.106). The cognitive subscale normal data was verified (K=.889, df=871, p=.147). The emotional factor was normality (K=.911, df= 871, p=.122).

The study examined outliers to assess the impact of the ongoing COVID-19 pandemic on university students' emotional, cognitive, and behavioral subscales. Since emotions fluctuate as individuals respond to epidemic-related changes, it wasn't feasible to exclude positive and negative outliers in the emotional subscale. Instead, the study utilized standardized values to account for outliers. The results are presented in Figure 1.

Since it is not possible to exclude positive and negative outliers in the emotional subscale, emotion is a temporary state of the individual that accompanies the changes of the epidemic. The study used the standardized values of the emotional subscale to get freed of the outliers.

The differences between genders and colleges in predicting the future expectation subscales of university students

MMANOVA analysis verified the effect of gender and the performance of college students in predicting future expectation subscales (emotional, cognitive, behavioral). The results were as in Table 3.

The results revealed the differences between the gender in predicting the future expectations of university students. The results also confirmed the existence of differences between the three colleges in predicting the future expectations of university students. The results showed the differences in emotional performance across gender (F = 6.96, p = .008). It also found differences between the three colleges in emotional performance (F = 5.74, p = .003).

Colleges differ in the expected performance due to the nature of learning in its form, which may depend on shared decision-making, or training and collective or collaborative practice, as in health colleges, and this is in agreement with the results of Wei *et al*. study[4]. Or that some colleges, in personal learning, need to practice skills after seeing direct experiences in practice, as in engineering colleges, and then need to overpower them and practice them individually[41,6].

The study found that there are statistically significant differences in the future expectations subscales. This result contradicts previous studies, as the expected performance depends on the nature of the use of educational technology in learning to enhance the skills of structured learning to respond to professional and academic life skills, and this is consistent with the study of Bahri *et al*. and Dabbagh and Kitsantas[23;24].

The correlation coefficient between the expected performance in future tasks among the university students

The correlation coefficients matrix was performed between the expected performance subscales of the university student considering the personal learning environment. Standardized scores were used to express emotional performance and the correlation coefficients were as shown in Table 4.

It turns out that there is an inverse correlation between the expectation of cognitive and behavioral performance, that is, despite the high level of knowledge of the learner, he feels that he needs field training in his field of specialization. The continuation of the Corona pandemic led to a crisis in practical work and the acquisition of direct experiences in practical applications. Students may also suffer from occupational anxiety because of their lack of confidence in the skills and behavioral aspects of their fields of specialization. Or that the nature of the study imposed by the university has led to a sudden shift in the performance of students in a way that made him need more practical training. The lack of practical training led to mastering the cognitive aspect as a compensating generation for the lack of practical training.

The correlation coefficient between the expectation of cognitive performance and emotional

Table 3: Descriptive statistics of future expectations subscale

	Emotional performance	Cognitive performance	Behavioral performance
Mean	38.48	47.09	25.85
Variance	43.11	150.75	161.79
Skewness	-.04	-.92	.71
Kurtosis	1.30	.06	.51

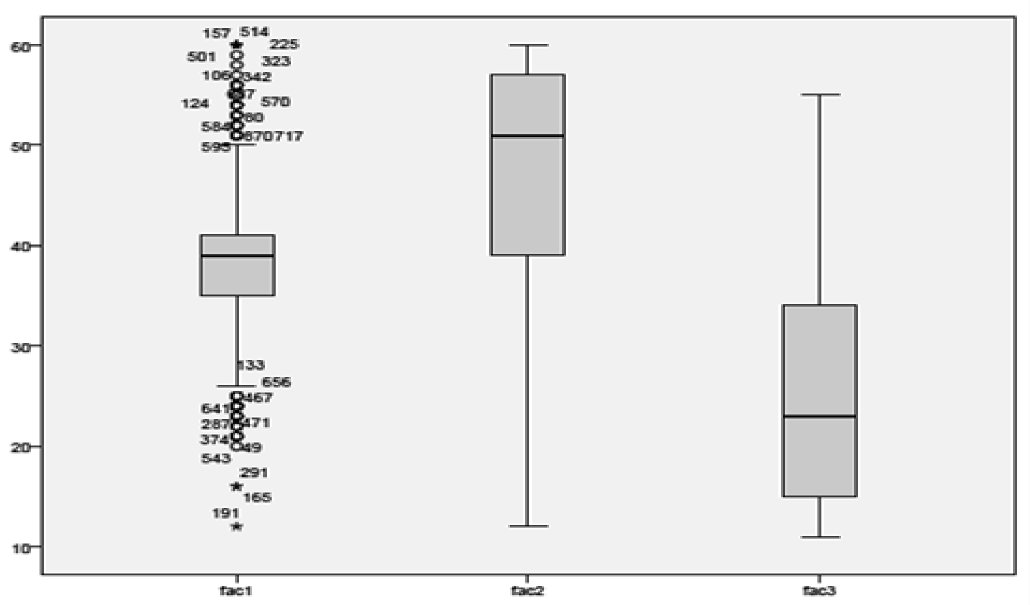

Figure 1: Positive and negative outliers of the future expectation subscales

Table 4: MMANOVA differences between genders and colleges

Effect	Value	F	Hypothesis df	Error df	Sig.
Intercept	20.048	5393.01	3	807	.000
Major	.017	2.237	6	1612	.037
Gender	.014	3.776	3	807	.010

Table 5: Correlation coefficients of expected performance subscales in future tasks

Factors	Cognitive	Behavioral	Emotional
Cognitive	1		
Behavioral	-.366 P=.000	1	
Emotional	.499 P=.000	.214 P=.000	1

performance was 0.50, which was a medium value, and this means that due to the negative general mood among university students, cognitive performance increases whenever the emotion is very negative, and this may be due to several factors, including fear of loss or fear of failure. Or fear of the future, or the level of internal motivation may be high, and the sample is very optimistic and more flexible to the current circumstances. The results resulted in a weak direct correlation coefficient between the expectation of emotional performance and behavioral performance. This means that although there is a weak correlation; However, the sample strives to acquire any types of behavioral skills that enhance professional performance after graduation. And that the increase in mood, negative emotion and anticipation of the worst leads to seeking field training and grabbing opportunities to conduct further training.

The previous results resulted in differences between the sexes and the performance of college students in predicting the expectations of the future tasks (emotional, cognitive, and behavioral) of university students[42]. The partial correlation coefficient is computed as a kind of statistical control procedure for the effect of gender and colleges. The results are as Table 5.

The correlation coefficient between predicting cognitive and behavioral performance was shrunk by 0.47 using the partial correlation coefficient. The relationship shrank from 0.50 to 0.47, which means it shrank at a rate of 0.03, which is a very weak rate. This means that despite the increase in the sample size of the female participants, and the females were characterized by the negative influence of emotion. The relationship shrank by a small amount when using the partial correlation coefficient. This contraction means that there is a Type I error in the emotional performance prediction dimension due to sample variance. Or training for both sexes was equal in cognitive performance, and the contraction may have occurred as a result of isolating the emotion resulting from the anxiety of using technology.

The average positive relationships between the cognitive and emotional dimensions are due to the similarity between past and present tasks. Fear as a result of anticipating the impression of others as a result of low performance as a result of personal learning may work on emotional fluctuation and this may agree with Fisher *et al*.[28].

While if those tasks are difficult to perform, the individual's motivation to complete the task may be those positive feelings formed to finish it, and this agree with Pekrun *et al*.[33]. Personal learning may lead to an increase in academic emotions that work on the learner's constant plan of the scientific material and reach the perceived pleasure of cognitive learning, and this is confirmed by Pekrun and Perry[41].

The future expectation is considered an indicator of the university student's fear of losing. Accordingly, the student depends on the value of the task he can be studied during personal learning situations. Since he may ignore some problems due to the lack of nature of its context, which makes him in terms of behavioral performance low as a result of lack of training on those tasks and this is what studies indicated[13,32].

The learner may possess sufficient knowledge, but the practice he obtained is insufficient. Consequently, controlling the tasks in the test situation is difficult as a result of anticipating failure. Cognitive performance is disturbed as a result of emotional arousal, and then the learner expects a decline in behavioral performance, and this was confirmed by Cottini, Basso and Palladino[12].

Personal learning sustainability gives opportunities to the learner in individual innovation as a result of his knowledge and his navigation and organization of knowledge[42]. Thus, the learner's motivation grows as a result of merging knowledge and adapting it to solve problems. Accordingly, emotion has nothing to do with the educational context in personal learning situations, and this is consistent with Bahri *et al*.[23]; Camacho-Morles *et al*.[32]; Horng *et al*.[29].

The result of isolating emotion from the educational context is the individual’s ability to link between the theoretical and practical aspects of personal learning. The individual can imagine and anticipate possible test scenarios in advance, this is consistent with Terrett *et al*.[31]. These results can be used educationally in that the individual's ability to solve problems leads to getting rid of academic emotions related to learning and testing situations. The expected behavioral performance of the learner in completing the tasks required of him is as high as possible. Also, academic emotions can direct learner motivation, and the shortcomings in the individual's cognitive performance increase the practice of skills and problem-solving.

Behavioral performance is associated with cognitive and motivational processes. Organized

Table 6: Partial correlation of expectation of future tasks components

Factors	Cognitive	Behavioral	Emotional
Cognitive	1		
Behavioral	-.367 P=.000	1	
Emotional	.466 P=.000	.217 P=.000	1

tasks opportunities should take advantage of during social comparison processes, and personal learning is in the opportunities for the learner to pursue learning materials on his own. Rather, it is through the summaries and generalizations that he receives from his colleagues at the highest level of achievement[6]. The learning environment improves the surrounding environment and this is in agreement with Orsini *et al*.[30]. In the case of isolating emotion from the learning context, they understand well, learn, analyze and link them and their parts together, the values of the partial correlation coefficient as a result of their treatment.

It can be derived fact which manages the personal learning environment works to suppress their emotion in light of increased learning motivation, sequencing in cognitive tasks, developing creativity opportunities, cognitive flexibility, and providing appropriate opportunities from changing feedback[42,43]. Personal learning can enhance the competitive abilities of the learner and thus improve the behavioral expectation of future performance, and this is consistent with Horng *et al*.[29], and Kupchyk and Litvinchuk[6].

From previous, the prediction of students' academic performance through the management of their personal learning environment is a varied and intricate field of study. The correlation between students' management of their learning surroundings and their eventual academic achievement has been the subject of numerous research. Previous research findings have substantiated the existence of a noteworthy association between proficient management of personal learning environments and enhanced academic performance in subsequent tasks. One of the most significant results from our research along with previous studies is that students who actively manage their personal learning environments perform better academically. This involves creating objectives, arranging study materials, using time management skills, asking for assistance when necessary[44,45], and reflecting on their learning progress. Students who take responsibility for their learning and create favorable study environments are likelier to succeed academically.

Discussion

The pandemic has had undeniable effects on education. The pandemic has created a huge social experiment about educational systems[2,39]. Authorities should take measures to rapidly solve problems in cases that the pandemic continues longer than expected or new pandemics arise, based on the analysis and interpretation of data, the following results were summarized according to the objectives of the study as follows: The effect of emotional state on expectations of future performance, cognitively and behaviorally.

The nature of the expectation for performance in future tasks is affected by the nature of the college study (engineering, humanities, medical). The effect of technology primarily affects the nature of the student’s expectation of his performance in the task due to the theoretical connection of his studies. As for medical colleges, studying through technology with problem-solving. The expectation of upcoming tasks is influenced by individual gender differences, professional role expectations, and problem-solving ability.

The academics’ skills and experiences defined their attitudes towards PLE from a distance during the Corona epidemic. So, providing technical assistance to support and improve the academics’ competencies is of importance. This will help students to have a more autonomous and personalized learning experience, allowing students to grasp the learning progress and choose the learning environment according to their knowledge and ability level.

To predict academic performance based on PLE management, it is important to assess three factors: First, the resources that a student utilizes, such as textbooks, internet resources, and social media, might reveal information about their learning styles and preferences. Second, the tools a learner employs to help them learn, such as productivity applications, note-taking apps, and collaboration tools, can have an impact on their academic success. Third, social network analysis: The structure and makeup of a learner's social networks, including the quantity and kind of connections, can reveal information about their learning environment and support systems. Analyzing these elements allows us to uncover patterns and trends in a learner's PLE management and forecast their future academic achievement.

Furthermore, our findings are consistent with previous research[44-46] demonstrating that the use of technology tools and digital resources in managing personal learning settings can improve academic achievement[46,47]. Learning management systems, online collaboration tools, educational apps, and digital note-taking programs can all help students organize knowledge, collaborate with peers, access resources, and measure their progress more effectively.

Conclusion

Predicting future academic achievement based on personal learning environment management is a difficult educational topic. Our PLE includes the resources, technologies, and social networks we utilize to learn. Analyzing and monitoring a learner's PLE can reveal their learning practices and performance and forecast their academic progress. A learner's academic success can be influenced by four elements, which are: (1) Cognitive capacities: The inherent cognitive capacities of a student, encompassing memory, attention, and problem-solving aptitude, might exert a substantial influence on their scholastic achievements. (2) Motivation: The academic success of a student can be influenced by their level of motivation and interest in the subject matter. (3) Learning strategies: The methods and approaches employed by a learner to acquire and assimilate knowledge can impact their academic achievement. (4) Social factors: The academic success of a learner can be influenced by their social environment, encompassing their interactions with peers and teachers.

The study recommends equal opportunities should be provided for both students and academics, and their access to the required technologies should be assured. LMSs and licensed external services should support thousands of simultaneous participants and offer various components/extensions to support instructional activities.

PLE from a distance during the Corona epidemic has led to remarkable changes in the students’ approaches to learning as well as the academics’ teaching methods. In modern distance education, digital tools take the forefront. Online training activities could be conducted to improve the academics’ knowledge and skills. There is also a greater need for educational institutions to strengthen the practices in the curriculum and make it more responsive to the learning needs of the students even beyond the conventional classrooms. Promote the reconstruction of ecological teaching model based on DL to develop PLE Skills. Future studies need to search how to make students learn more autonomously in online teaching and develop their PLE, teacher teaching is more effective, and online teaching models are more reasonable; Also, how to make home education and school education more closely linked through online learning. Future studies should also focus on the factors which are critical from the point of view of students to accept this online learning during the pandemic COVID19.

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Ethical approval

All procedures performed in the study followed the ethical standards of the institutional research committee of the Deanship of Scientific Research at the University of Hail (RG-21016) and with the 1964 Helsinki declaration and its later amendments.

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Data availability statement

The raw data supporting the conclusion of this article will be available upon request to the corresponding author.

Compliance with ethical standards

We have no conflicts of interest to disclose. Data available on request from the authors.
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Declaration and copyright terms

We (I), Badr A. Alharbi, Usama M. Ibrahem, Mahmoud A. Moussa' Mona A. Alrashidy, and Bahgat A.Radi, the author (-s) of the paper entitled '***The Shift to Personal Learning Environment has been Fruitful- Predicting Performance in Future Tasks Based on Personal Learning Environment Management during the Corona Epidemic***' declare that: this manuscript is an original scientific paper, and the manuscript has not been published in other journal.

Contribution of authors

Dr. Usama M. Ibrahem: originator of the concept, assumptions, methods, editing, Conclusion.
Dr. Badr A. Alharbi: Procedure and prepare tools, Discussion, Conclusion.
Dr. Mahmoud A. Moussa: prepare tools, statistics, Delimitations.
Dr Mona A. Alrashidy: Methodology, Literature review,
Dr Bahgat Attia.Radi: originator of the concept, Research motivation and problem.

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