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Factors influencing online learning fatigue among blended learners in higher education

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Highlights

- This study investigates the factors influencing online learning fatigue among blended learners in higher education amid the post-pandemic era.
- Online query data can be used to predict influencing factors of blended learners in online learning settings in response to reasons of fatigue in the post-pandemic era and regression results supports a valid three-level construct of Online Learning Fatigue Scale.
- The findings support the notion that women are more prone to be fatigued in online learning settings, even if there is no statistically significant difference in terms of gender.
- By contributing to the body of knowledge on fatigue, the Online Learning Fatigue Scale provides a measurement model that is both reliable and valid for assessing fatigue in online and blended learning settings.

Abstract

This cross-sectional study aims to investigate the factors influencing the levels of online learning fatigue among blended learners in higher education amid the post-pandemic era. In this context, a total of 347 college students voluntarily completed an online questionnaire, including the Online Learning Fatigue (OLF) Scale, to determine the fatigue levels and to examine the three-level construct of the OLF. The gender preference in the seven OLF subscales supported the literature that women are more prone to be fatigued. Additionally, the findings supported the structural relationships between the seven factors of the three-level construct of the OLF and produced results that support the theoretical framework for the model to scrutinize online learning fatigue levels in higher education. The regression analysis results supported that information equivocality was a significant predictor of information overload, and that the system complexity and system pace of change were significant predictors of system feature overload. Finally, it supported the three-level construct of the OLF, supporting the notion that system feature overload, communication overload, and information overload are significant predictors of LMSs fatigue. Considering the limitations, the factors that should be addressed to form well-structured online learning settings are scrutinized, and theoretical and practical implications are discussed.

Article Info: Research Article

Keywords: *Online learning fatigue, Risk factors, Blended learners, Higher education*

1. Introduction

Individuals consume almost 34 gigabytes of data per day, according to findings from a stunning ten-year-old study based on daily data consumption (Bohn & Short, 2012). Furthermore, it has been stated that this growth is approximately rate of 5.4% every year. Based on these statistics, the quantity of data exposed for the average individual nowadays surpasses about 75 gigabytes. Therefore, it is possible to assert that the volume of data in question has reached alarming proportions nowadays. So, this circumstance has a variety of precipitating factors. Individuals' media consumption habits are being severely influenced by the

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diversity of technological instruments, the rapidity of the technological transformation process, and the higher usage levels of diverse communication venues (Koc & Barut, 2016; Zhong et al., 2011). Researchers assess problematic media consumption patterns and habits as a problem that needs to be addressed as well as a significant risk factor for learners who are enrolled in higher education (Oducado et al., 2021a; Oducado et al., 2022; Tuğtekin, 2022b). During the zenith of the COVID-19 pandemic, widespread social distance restrictions prevented face-to-face interactions and, on the contrary, catalyzed the further popularity of various video conferencing platforms (Ngien & Hogan, 2022). This circumstance has hastened the increase in the amount of data that individuals must cope with on a daily basis. The rapid transformation process in computer-based communication technologies has also generated substantial changes in interpersonal communication, socializing, and naturally educational environments due to the excessive use of Information and Communication Technologies (ICTs) (Salehan & Negahban, 2013). However, the urgent crisis management strategy brought on by the COVID-19 pandemic has negatively impacted distance education strategies, which have now turned into a must rather than an option (Barut Tuğtekin, 2021; Bozkurt & Sharma, 2020; Wang, 2022). Although it has various potential positive aspects such as maintaining the continuity of education and being one of the most effective solutions in urgent crisis management, the negative factors arising from Emergency Remote Teaching (Bozkurt & Sharma, 2020) have been mostly ignored by field experts, educational researchers, and instructional designers (Tugtekin, 2022a). Compared to prior years, the change in pedagogy appears to have been accelerated and triggered more quickly by the COVID-19 pandemic as an educational disruptor (Barber & Sher, 2022; Thurston, 2021). Considering the pandemic's effects today, it is crucial to carefully consider the potential risk factors associated with the usage of problematic technology.

2. Literature

2.1. Information and Communication Technologies (ICTs) and Overload

ICTs play an important role in the development and implementation of internet-based products and services, and they provide significant contributions to communities to improve living conditions. On the other hand, the problematic usage of ICTs impacts how densely communication occurs in daily life, and naturally, it is inevitable that this would have a detrimental effect on individuals by overloading them (Batista & Marques, 2018). In recent years, parallel to the facilitation of communication opportunities, the enormous amount of daily information and the outcomes of the enormous amount of information that individuals are exposed to (Eppler, 2015; Tugtekin et al., 2020), have recently led to the formation of awareness on the subject Lee et al., 2016; Tuğtekin, 2022b) and the search for solutions for the issue of information overload (Batista & Marques, 2018). Although it is believed that information overload merely affects individuals, it has the potential to result in major problematic scenarios that might cause organizational and social issues. It has been claimed that information overload has an effect on individuals' motivation, mood, and emotions (Bawden & Robson, 2009), may have a detrimental effect on an organization's performance and productivity (Ellwart et al., 2015), and may have a direct or indirect effect on the standard of judgments, behavioral patterns, and societal norms among various stakeholders (Batista & Marques, 2018). Additional risk factors include poor time management, limited information processing capacity, a lack of ability to filter and prioritize information, unproductive communication strategies, and low-level technology use abilities (Haase et al., 2016; Tugtekin et al., 2020; Tuğtekin, 2022b). Environment-related factors can also have an effect on information and communication technology overload (Lee et al., 2016; Tuğtekin, 2022b; Zheng & Lee, 2016). In other respects, females are more likely to experience fatigue when an assessment of information and communication technology use is performed in the context of gender because they experience greater levels of information and communication technology overload than males (Jenaro et al., 2007; Salim et al., 2022; Takao et al., 2009; Tugtekin et al., 2020; Tuğtekin, 2022b). In brief, a variety of risk factors might define ICTs' related overload and fatigue.

On the other hand, it should not be overlooked that there is a growing trend in video conferencing and online learning sessions in communication networks utilized in educational settings, which comes with it a number of risk factors (Salim et al., 2022). Communication networks that are chosen in educational settings are organized in the structure of Learning Management Systems (LMSs) (Barut Tuğtekin, 2021; Cavus, 2015; Paulsen, 2003). It is reasonable to assume that many users of LMSs will exhibit indications of fatigue given the amount of time and duration they spend using them (Batista & Marques, 2018; Islam et al., 2020; Salim et al., 2022). Since duration is one of the key factors contributing to the overload (Batista & Marques, 2018; Tushman & Nadler, 1978), its significance is made clear by contrasting the amount of data that can be used to make decisions over a certain period with the quantity of data required to accomplish a given operation in that same time (Barut Tugtekin, 2022; Batista & Marques, 2018; Tuğtekin, 2022b). It is advised not to neglect the nature of the information characteristics (e.g., equivocality, complexity, etc.) and information processing procedures in addition to the time and duration factors (Eppler, 2015; Tugtekin et al., 2020). Thus, information characteristics are crucial and critical.

The Stress-Strain-Outcome (SSO) Model (Koeske & Koeske, 1993) is utilized as a theoretical framework in this study to better understand the etiology of information overload avoidance strategies among users of LMSs. The SSO model is commonly used to investigate fatigue, stress, and stress-inducing factors (Ayyagari et al., 2011; Barber & Sher, 2022; Lee et al., 2016; Patton & Tuke, 2022; Tugtekin, 2022a; Tugtekin et al., 2020). On the other hand, LMSs fatigue occurs when learners' capacity to process information is exceeded by the amount of information they must process while participating in activities (e.g., LMSs sessions and video conferencing sessions) that they engage in through LMSs (Tugtekin, 2022a). Because the Limited Capacity Model (LCM) stresses the fact that individuals have a limited capacity available for processing information (Lang, 2000). Due to various issues and limits in information processing capacity, learners who try to handle the overwhelming amount of information they come across in online learning settings eventually become fatigued and overloaded. When the LCM and SSO models are considered together, learners should be able to manage the volume of information. Because the issue of fatigue is brought up by learners' usage patterns, and habits that are incapable of appropriate time management. On the other hand, the Person-Environment Fit Model (Lazarus, 1966; Lazarus & Folkman, 1984) and Cognitive Behavior Theory (Alford & Beck, 1997; Beidel & Turner, 1986; Zheng & Lee, 2016) should be used as a framework to investigate the focus of assessments on the impact of activities on LMSs fatigue. Furthermore, individuals' information preferences, communication rates, and processing timeframes have the potential to cause fatigue (Cho et al., 2011). For example, improvements to the interface of the LMSs or the addition of new capabilities or features to the system might become a compelling reason for learners. Since LMSs are also social networking platforms, the fatigue model on social networking services examined and validated by Lee et al. (2016), and for online learning environments and re-conceptualized by Tugtekin (2022a) have been validated amid the COVID-19 pandemic. It is feasible to conclude from this perspective that, given the post-pandemic settings, learners with obsessive LMSs usage patterns and habits are extremely vulnerable to information overload and fatigue (Nesher Shoshan & Wehrt, 2022).

To sum up, during the COVID-19 pandemic, the rapid and relatively mandatory integration of various LMSs into distance learning environments or online learning-based programs has catalyzed the need to assess the potential challenges and risk factors faced by learners who participate in distance education (Hisey et al., 2022; Tugtekin, 2022a). The fundamental cause of this is that, in pandemic settings, online learning has replaced traditional classroom instruction as a need rather than an option (Bozkurt & Sharma, 2020; Elbogen et al., 2022; Fırat & Bozkurt, 2020; Xie et al., 2021). Although there are various practical benefits, such as urgent crisis management, guaranteeing academic continuity, and being the most practical answer available, some drawbacks of distance education and ERT should not be overlooked by the field expert, practitioners, and policymakers. College students are said to be particularly affected by the pandemic change since they are exposed to greater screen time duration and video conferencing for their educational needs (Guo et al., 2021). On the other hand, since college students are the most productive age group and have more freedom to choose their workplaces (Alcalá, 2014; Barut Tugtekin & Koc, 2020; Caglar et al., 2017), it was preferred to focus on college students in the current study because their levels of fatigue could have a higher detrimental effect on their productivity (Picton & Kahu, 2021; Tugtekin et al., 2020). In summary, the gap in the literature is the necessity to carefully investigate the problematic technology use behavior patterns caused by pandemic settings in today's post-pandemic situations, particularly in higher education. The present study was conducted on the preliminary study by Lee et al. (2016), who provided the SNS Fatigue model based on the theoretical framework of the SSO Model, and Tugtekin (2022a), who validated this modified model for online learning environments, to address the post-pandemic settings' gap and contribute to the Educational Technology and Online Learning (ET/OL) literature. Hence, it is critical to scrutinize the LMSs Fatigue investigated in the current study in higher education and in post-pandemic settings, as it has the potential to extend the ET/OL literature.

2.2. Purpose and Rationale

The current study, which is based on the abovementioned literature, aims to scrutinize the LMSs fatigue levels of college students who are enrolled in higher education programs that combine online and face-to-face learning, to examine the relationship between variables of interest, to identify the factors that contribute to online learning fatigue, and to clarify the conceptual model for LMSs fatigue. The Online Learning Fatigue (OLF) Scale by Tugtekin (2022a) defines the 7-factor structure that is presented in the model. The model was revised and re-validated by Tugtekin (2022a) for online learning fatigue based on Lee et al. (2016)'s SNS fatigue model. Each contributing factor to fatigue from blended learning was also scrutinized in terms of gender. To examine the construct of the model validated by Tugtekin (2022a), in post-pandemic period, the following hypotheses (H) were tested.

H1. Information Equivocality can significantly predict learners' Information Overload dispositions.

H2. System Pace of Change (H2a) and System Complexity (H2b) can significantly predict learners' System Feature Overload dispositions.

H3. Learners' Information Overload (H3a), Communication Overload (H3b), and System Feature Overload (H3c) dispositions can significantly predict learners' LMSs Fatigue.

3. Methodology

3.1. Research Design, Participants, and Data Collection Procedure

To clarify the predictors of online learning fatigue, the quantitative cross-sectional research design (Fraenkel et al., 2012) was preferred. The research design allows for the testing of potential relationships between variables of interest as well as the evaluation of each variable's existing states (Büyüköztürk et al., 2018; Karasar, 2015).

The online data collection form used in the research consists of two sections. The first section includes information on the participants' demographics, such as gender, department, and grade level, as well as the amount of time spent in online learning environments. The Turkish version of the "Online Learning Fatigue (OLF) Scale" developed by Tugtekin (2022a), which consists of 7 factors and 28-items in a 7-point Likert type, was utilized in the second section. The measurement tool explains 62.4% of the total variance and the Cronbach's Alpha (α) internal consistency coefficient value calculated for the overall was found to be 0.887. The increase in measurement tool scores corresponds to an increase in online learning fatigue. The measurement tool has a reliable and valid measurement model, which has been tested and confirmed (Tugtekin, 2022a).

In Table 1, the variables of the measurement tool's original form, the item's standardized factor loadings, the composite reliability values, and the values for Cronbach's Alpha's (α) internal consistency coefficient are all listed.

Table 1.
Original values of Online Learning Fatigue Scale (Tugtekin, 2022a)

Factor	Items	Factor Loading	Mean	SE	SD	*t*	Variance Explained	CR	α
Information Equivocality	EQC1	.702	5.47	.079	1.435	10.79*	9.724%	0.716	0.715
	EQC2	.770	5.10	.080	1.454	11.75*			
	EQC3	.785	5.53	.076	1.369	12.18*			
System Pace of Change	SPC1	.644	5.35	.079	1.434	13.07*	10.623%	0.791	0.788
	SPC2	.791	4.54	.089	1.605	12.41*			
	SPC3	.661	4.71	.091	1.641	11.17*			
	SPC4	.721	4.48	.091	1.641	12.60*			
System Complexity	SCX1	.818	3.36	.092	1.657	5.24*	6.029%	0.779	0.769
	SCX2	.536	3.20	.096	1.739	8.53*			
	SCX3	.628	2.31	.086	1.563	5.46*			
Information Overload	INO1	.661	3.20	.093	1.687	18.39*	6.424%	0.798	0.758
	INO2	.745	3.05	.091	1.654	14.57*			
	INO3	.628	2.86	.087	1.582	9.72*			
Communication Overload	CMO1	.561	5.14	.085	1.540	7.50*	9.472%	0.788	0.784
	CMO2	.491	3.36	.098	1.767	9.66*			
	CMO3	.640	4.60	.098	1.774	14.29*			
	CMO4	.368	4.60	.088	1.587	4.85*			
	CMO5	.584	4.31	.101	1.818	14.77*			
System Feature Overload	SFO1	.423	4.23	.905	1.714	12.68*	5.501%	0.781	0.774
	SFO2	.405	2.94	.089	1.618	5.72*			
	SFO3	.663	3.86	.092	1.672	7.81*			
	SFO4	.459	3.60	.096	1.741	15.75*			
	SFO5	.490	3.64	.100	1.810	8.46*			
LMSs Fatigue	LMS1	.710	3.81	.103	1.817	16.76*	14.640%	0.859	0.855
	LMS2	.801	3.37	.099	1.788	14.69*			
	LMS3	.820	3.37	.103	1.854	19.13*			
	LMS4	.542	3.25	.099	1.789	9.90*			
	LMS5	.790	2.92	.097	1.761	16.07*			

Note. *$p < .001$

The participants' active participation in both online and face-to-face learning settings was established as the intact inclusion criteria for the study. According to this criterion, a total of 347 college students voluntarily participated. Following univariate and multivariate outlier analysis, it was decided to exclude a total of 14 participants who had outliers from all ongoing analyses. As a result of the outliers filtering, the data set was produced by the responses of a total of 333 college students [n_{female}=202, (60.7%); n_{male}=131, (39.3%)] aged 19 to 25 (*SD*=2.09). Table 2 provides information on the demographic profiles of the participants.

Table 2.
Demographic profiles

	Female		Male		Total	
	f	%	*f*	%	*f*	%
Departments (Faculty of Education)						
Turkish Language Education	20	9.9	43	32.8	63	18.9
English Language Education	47	23.3	28	21.4	75	22.5
Guidance and Psychological Counseling	34	16.8	14	10.7	48	14.4
Early Childhood Education	39	19.3	12	9.2	51	15.3
Primary School Mathematics	20	9.9	27	20.6	47	14.1
Classroom Education	42	20.8	7	5.3	49	14.7
Total	202	100	131	100	333	100
Grade Levels						

Freshman	-	-	-	-	-	-
Sophomore	106	52.5	39	29.8	145	43.5
Junior	96	47.5	92	70.2	188	56.5
Senior	-	-	-	-	-	-
Total	202	100	131	100	333	100

Table 3 presents the average daily allotted duration of participants in online learning environments as well as their engagement in video conferencing sessions.

Table 3.
The frequency of time participants spends each day participating in videoconferencing and online learning sessions

	Female		**Male**		**Total**	
	f	%	*f*	%	*f*	%
Frequency of Average Daily Time Allotted for Online Learning Sessions						
1 hr or less than 1 hr	-	-	-	-	-	-
More than 1 hr – Less than 2 hr	9	4.5	9	6.9	18	5.4
More than 2 hr – Less than 3 hr	54	26.7	47	35.9	101	30.3
More than 3 hr – Less than 4 hr	78	38.6	42	32.1	120	36.0
More than 4 hr – Less than 5 hr	61	30.2	33	25.2	94	28.2
5 hr or more than 5 hr	-	-	-	-	-	-
Total	202	100	131	100	333	100
Frequency of Average Daily Time Allotted for Video Conferencing Sessions						
1 hr or less than 1 hr	-	-	-	-	-	-
More than 1 hr – Less than 2 hr	15	7.4	19	14.5	34	10.2
More than 2 hr – Less than 3 hr	77	38.1	45	34.4	122	36.6
More than 3 hr – Less than 4 hr	70	34.7	46	35.1	116	34.8
More than 4 hr – Less than 5 hr	40	19.8	21	16.0	61	18.3
5 hr or more than 5 hr	-	-	-	-	-	-
Total	202	100	131	100	333	100

To identify the video conferencing platforms and device types they frequently prefer; participants were asked to provide percentage-frequency values. The results are shown in Table 4 along with the results. Due to the presence of more than one video conferencing platform account and technological device preferred by the participants, the total value for these values was not calculated.

Table 4.
Frequently preferred videoconferencing platforms and device types

	Female		**Male**		**Total**	
	f	%	*f*	%	*f*	%
Videoconferencing platforms						
Zoom	184	91.1	114	87.0	298	89.5
Microsoft Teams	161	79.7	107	81.7	268	80.5
Google Meet	183	90.6	121	92.4	304	91.3
GoToMeeting	19	9.4	9	6.9	28	8.4
Adobe Connect	81	40.1	58	44.3	139	41.7
Perculus Plus	29	14.4	22	16.8	51	15.3
Cisco Webex	6	3.0	2	1.5	8	2.4
BigBlueButton	41	20.3	15	11.5	56	16.8
Diğer	10	5.0	4	3.1	14	4.2
Device types						
Smartphones	196	97.0	127	96.9	323	97.0
PC	103	51.0	71	54.2	174	52.3
Tablet PC	12	5.9	7	5.3	19	5.7

The most popular video conferencing services among the participants are Google Meet (91.3%), Zoom (89.5%), and Microsoft Teams (80.5%), respectively, according to an analysis of the platforms they use most frequently. Additionally, it becomes clear by looking at the preferred device types among the participants that smartphones (97.0%), PC (52.3%), and Tablet PC (5.7%), respectively have the utilization rates. It is noteworthy that tablet PC usage rates are quite low.

3.2. Data Analysis Procedure

To analyze the data collected via the online data collecting form, SPSS 24.0 software was chosen. The data analysis uses descriptive statistical methods. It was found that all the variables evaluated in the study did not violate the assumption of normal distribution by computing and scrutinizing the skewness and kurtosis values for each variable of interest (i.e., ±2; George & Mallery, 2010). The assumption of normal distribution, the investigation of univariate and multivariate outlier values (i.e., Mahalanobis Distance values), and the indicated prerequisites for the relevant parametric tests were all reviewed in the evaluations for the whole data set, and no violations were found. Considering this, the dataset is appropriate for ongoing analyses.

3.3. Findings

To ascertain the participants' levels of online learning fatigue, descriptive statistics were produced for the average of each factor. The results are shown in Table 5.

Table 5.
Learners’ scores on each factor of Online Learning Fatigue

	n	Min	Max	Mean	*SD*	Skewness	*SE*	Kurtosis	*SE*
Online Learning Fatigue Scale									
Information Equivocality	333	8	21	5.383	0.901	-.706	.134	.332	.266
System Pace of Change	333	9	28	4.895	1.026	-.362	.134	-.521	.266
System Complexity	333	3	17	2.889	1.060	.245	.134	-.545	.266
Information Overload	333	3	19	4.722	1.212	.256	.134	-.655	.266
Communication Overload	333	9	32	4.465	0.931	-.332	.134	-.455	.266
System Feature Overload	333	7	29	3.596	0.945	.071	.134	-.569	.266
LMSs Fatigue	333	5	35	3.274	1.260	.303	.134	-.717	.266

The measurement tool yields a total score range between 28 to 196, with 28 being the lowest possible value, and 196 being the maximum. Based on the data in Table 5, it is clear that the participants' average scores for information equivocality (Mean=5.383; *SD*=.901) factor is high, while the system pace of change rate (Mean=4.895; *SD*=1.026), information overload (Mean=4.722; *SD*=1.212), communication overload (Mean=4.465; *SD*=.931), system feature overload (Mean=3.596; *SD*=.945), and LMSs fatigue (Mean=3.274; *SD*=1.260) factors are moderate. Contrarily, the system complexity average score was found to be low (Mean=2.889; *SD*=1.060).

Additionally, the OLF scores of the participants were also examined in terms of gender. A t-test was conducted to evaluate if there were statistically significant differences in the degrees of online learning fatigue among individuals who received blended learning experience. In Table 6, test results are presented.

Table 6.
Scrutinizing of Online Learning Fatigue levels pertaining to gender

Factors	Group	*n*	Mean	*SD*	*df*	*t*	*p*	*np*^{2}	*power*
Information Equivocality	Female	202	5.419	0.847	331	.899	.370	.002	.146
	Male	131	5.328	0.979					
System Pace of Change	Female	202	4.979	1.038	331	1.847	.066	.010	.453
	Male	131	4.767	0.997					
System Complexity	Female	202	2.897	1.019	331	0.166	.868	.001	.053
	Male	131	2.877	1.125					
Information Overload	Female	202	4.724	1.194	331	1.051	.959	.001	.050
	Male	131	4.717	1.244					
Communication Overload	Female	202	4.520	0.949	331	1.348	.179	.005	.269
	Male	131	4.380	0.899					
System Feature Overload	Female	202	3.616	0.955	331	0.489	.625	.001	.078

	Male	131	3.564	0.933					
LMSs Fatigue	Female	202	3.307	1.254	331	0.601	.548	.001	.092
	Male	131	3.223	1.271					

It is clear that no factor showed a statistically significant difference pertaining to the gender variable (i.e., $p>.05$; *ns*), according to the results of the t-test in Table 6. On the other hand, even though there is no statistically significant difference, it is clear from looking at the results that the average score for each factor is against the female participants (i.e., higher average scores for females).

3.4. Scrutinizing the Relationship Between Variables of Interest

A correlation analysis was conducted to determine the relationship between the factors of participants' online learning fatigue levels and the duration of their participation in online learning sessions and video conferencing sessions. In Table 7, the results are shown.

Table 7.
Correlation analysis results

	Information Equivocality	System Pace of Change	System Complexity	Information Overload	Communication Overload	System Feature Overload	LMSs Fatigue
Time Allotted for Online Learning Sessions	-.016	.034	.027	.015	.151**	-.047	.047
Time Allotted for Videoconferencing	-.022	.022	.073	.065	.189**	-.016	.088

Note. ** $p<.01$

As shown in Table 7, there is a statistically significant and positive correlation ($r=.151$; $p<.01$) between the amount of time allotted to online learning sessions and the communication overload factor. What is more, there is a significant correlation ($r=.189$; $p<.01$) between the time allocated to video conferencing sessions and the communication overload factor. It is revealed that the correlations between the variables that were determined to be statistically significant represent the correlation values of low-level (Cohen, 1988). Besides, it is noteworthy that there was no statistically significant correlation ($r=.047$; $p>.05$) between the time allotted for online learning settings and LMSs fatigue.

3.5. Regression Analyzes and Results

Regression analysis was conducted to test the hypotheses (H) investigated in the present study, and the results are compiled in Table 8. As shown in Table 8, in a significant regression model ($F_{(1,331)}=.780, p<.01$), with an explained variance rate of 23% ($R^2_{adjusted}=.230$), the information equivocality predicted information overload in a statistically significant and positively ($\beta=0.650$, $t_{(331)}=8.830$, $p<.01$, $pr^2=.230$). As a result, the H1 hypothesis was confirmed and supported.

On the other hand, a significant regression model ($F_{(2,330)}=107.433$, $p<.001$) with a 39% explained variance rate ($R^2_{adjusted}=.391$) found that the factors of system pace of change ($\beta=.239$, $t_{(330)}=6.030$, $p<.001$, $pr^2=.099$) and system complexity ($\beta=.494$, $t_{(330)}=12.902$, $p<.001$, $pr^2=.335$) factors positively and statistically significantly predicted the system feature overload factor. Therefore, H2a and H2b were supported.

Lastly, in a significant regression model ($F_{(3,329)}=115.140$, $p<.001$) with 50% explained variance ($R^2_{adjusted}=.508$), information overload ($\beta=.499$, $t_{(329)}=9.628$, $p<.001$, $pr^2=.219$), communication overload ($\beta=.133$, $t_{(329)}=2.324$, $p<.001$, $pr^2=.016$), and system feature overload ($\beta=.345$, $t_{(329)}=5.229$, $p<.001$, $pr^2=.051$) factors were found to be statistically significant and positive predictors of LMSs fatigue. The study's H3a, H3b, and H3c hypotheses were therefore also supported.

Table 8.
Regression analyses and hypotheses results

Predicted	Predicting	*SE*	*β*	T	Tolerance	VIF	Adjusted R^2	Hypothesis testing
Information Overload	Information Equivocality	.074	.650	8.830**	1.000	1.000	.230	H1 supported
System Feature Overload	System Pace of Change	.040	.239	6.030***	.995	1.005	.391	H2a supported
	System Complexity	.038	.494	12.902***	.995	1.005		H2b supported
LMSs Fatigue	Information Overload	.052	.499	9.628***	.597	1.676	.508	H3a supported
	Communication Overload	.057	.133	2.324***	.835	1.198		H3b supported
	System Feature Overload	.066	.345	5.229***	.606	1.650		H3c supported

Note. ***p<.001; **p<.01; *<.05

In conclusion, it is acknowledged that the research supports each hypothesis put out within its purview. Figure 1 presents the statistically significant correlations revealed by the regression analysis.

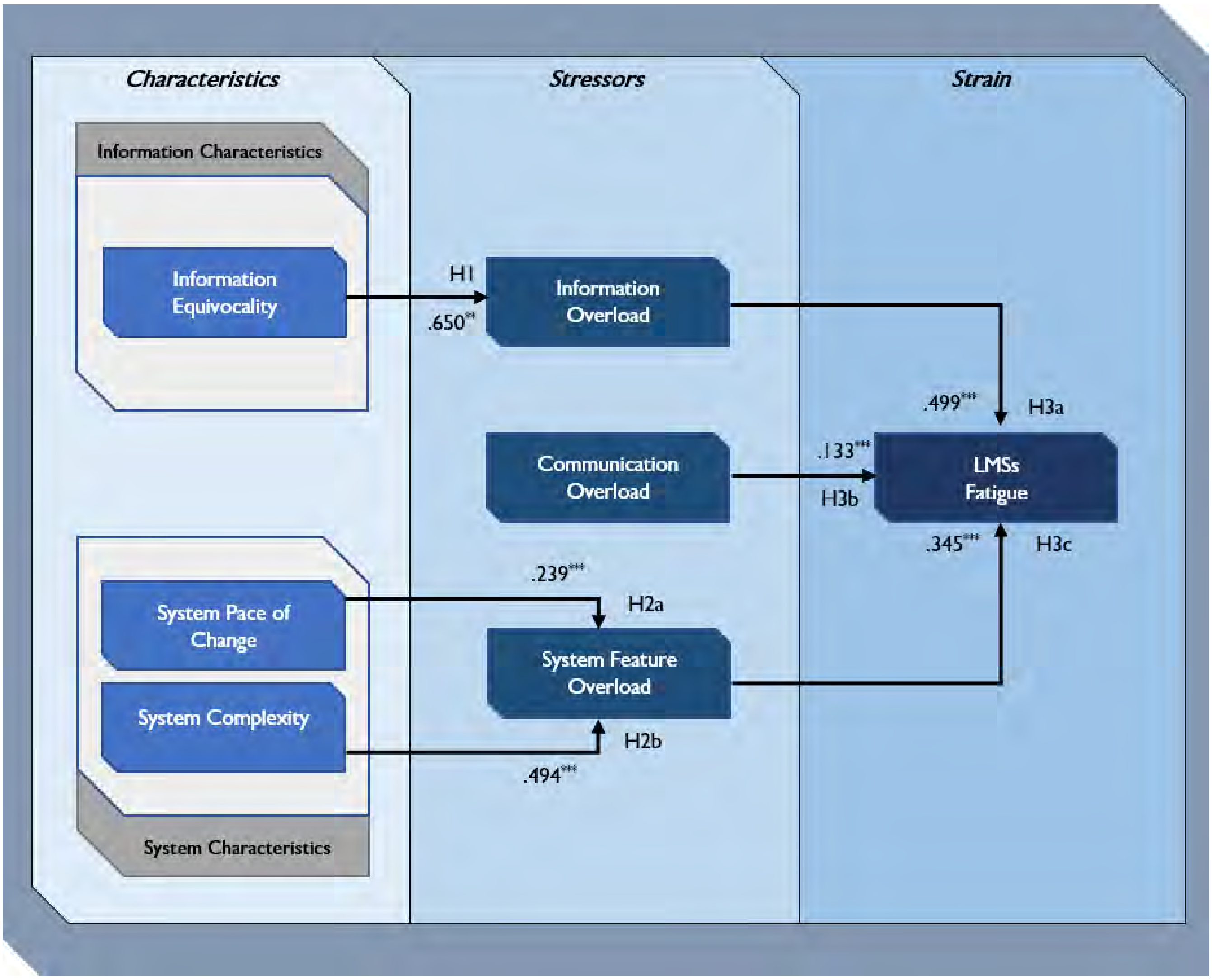

Fig. 1. Confirmed construct for the framework of OLF (Tugtekin, 2022a)

3.6. Discussion

The online learning fatigue levels of blended learners in higher education were examined in this cross-sectional study, and the validated online learning fatigue model was tested. As theoretical frameworks in the study, the SSO Model (Koeske & Koeske, 1993), Limited Capacity Model (Lang, 2000), Person-Environment Fit Model (Lazarus, 1966; Lazarus & Folkman, 1987), and Cognitive Behavior Theory (Alford & Beck, 1997) are utilized to scrutinize the etiology of factors that lead LMSs users to be subjected to information overload in higher education. Gender, online learning session durations, and video conferencing session durations were all investigated within the scope of the study. The evaluation of OLF levels by gender confirms the notion that women are more prone to be fatigued (Salim et al., 2022; Takao et al., 2009) in online learning settings, due to higher average scores for each factor of OLF. The literature supports the notion that "mirror anxiety" is one of the main causes of women's increased sensitivity to fatigue (Butler et al., 2012; Chandra & Issac, 2014), as well as the existence of low-level appearance satisfaction (Harriger & Pfund, 2022; Pikoos et al., 2022; Ratan et al., 2022), and social interaction issues (Bailenson, 2021; Fauville et al., 2021; Hopstaken et al., 2015; Ngien & Hogan, 2022; Synder, 1974; Zavotsky & Chan, 2016;). Based on theoretical assumptions, although LMSs fatigue increased during the COVID-19 pandemic, research findings suggest that similar effects are also in question in post-pandemic hybrid environments.

In the current study, the duration allotted to online learning sessions and video conferencing sessions, as well as the correlations between the OLF factors, were scrutinized. Surprisingly, it was obtained that there was no significant correlation between LMSs Fatigue, and the amount of time spent in online learning settings. This finding contradicts the results of various studies conducted during the pandemic period (for a review please see, Bailenson, 2021; Elbogen et al., 2022; Oducado et al., 2021b; Shockley et al., 2021; Tufvesson, 2020). Contrarily, research demonstrates that meeting size, duration, and the presence of the supervisor have no effect on fatigue levels (Cohen et al., 2011; Shosan & Wehrt, 2021), even when there is fatigue, appear to be consistent with the current findings. However, the fact that none of the research listed here was productivity-focused should not be overlooked. On the other hand, it was discovered that there was a significant correlation between Communication Overload and the amount of time spent in videoconferencing and online learning sessions. Thus, this finding, therefore, has the potential to have significant implications for instructional designers, and distance education researchers.

Furthermore, the regression analysis results supported the proposed three-level relational framework for the structure of the OLF, allowing us to retain all hypotheses (i.e., H1, H2, and H3). The first-level relational framework consists of Information Equivocality, System Pace of Change, and System Complexity (Tugtekin, 2022a), categorized as “characteristics.” The second-level relational framework consists of Information Overload, Communication Overload, and System Feature Overload (Lee et al., 2016; Tugtekin, 2022a), categorized as “stressors.” The third-level relational framework, categorized as “strain”, consists of only the LMSs Fatigue factor. Each first-level factor was able to predict each second-level relational framework, implying that all second-level factors could be determined by first-level factors (except for Communication Overload). In other words, information characteristics and system characteristics are the fundamental and crucial elements of stressors. It is also possible to state that the information equivocality, system pace of change, and system complexity are the prerequisites of the factors that cause stressors. Therefore, information characteristics and system characteristics should not be overlooked in the construction of online learning fatigue and online learning-related curricula. On the other hand, the relational and conceptual framework scrutinized in the present study can be applied to online learning-related curriculum designs. Due to the importance of the subject, further research could examine the association to the online learning fatigue notion in a large sample or distinct populations using more in-depth statistical analysis techniques, such as structural equation modeling, to extend the body of knowledge. Moreover, learners who use LMSs, which are constantly connected communication platforms, should be physically and psychologically prepared for the large number of information demands posed by the distance education process, as well as develop their self-regulated learning skills (Tugtekin, 2022a). In practical terms, one of the most significant contributions of the current study is that it underlines the significance of assessing fatigue levels in online learning environments and promotes additional investigation of the fatigue literature in higher education. The data gathered from learners' fatigue levels because of their excessive online learning settings could provide several suggestions for enhancing quality standards for distance education settings, LMSs, and design characteristics (Toney et al., 2021).

3.7. Limitations and Future Directions

It is crucial to consider the limitations mentioned here in the interpretation of the findings obtained from the current research. By analyzing the degrees of online learning fatigue among Turkish students enrolled in undergraduate programs, the research seeks to add to the body of knowledge in this area. The study's participants are faculty of education students who are enrolled in a variety of state universities across three distinct geographical regions. Therefore, it would not be the correct approach to generalize the findings of the present study to all college students. Cross-sectional and longitudinal studies should be carried out with study groups or samples who had several characteristics in common with similar and differing qualifications to overcome this limitation. In addition, the case should not be overlooked that the sample had a higher proportion of females. Because rigorous statistical testing was preferred in data analysis processes, the study's findings have robust and valuable implications for researchers seeking to investigate potential risk factors arising from time spent in online learning environments and videoconferencing sessions but have several limitations in terms of possible prevention and intervention strategies. It is persistently advised that the design elements be created in a way that does not encourage the compulsive or problematic usage patterns of the users, considering the organizational structures and social functions of LMSs. Furthermore, further research on other risk factors that may cause online learning fatigue levels, determining what prevention and intervention strategies might be, and developing a measurement model for learners at all levels of education (including K-12) responsible for the online learning curriculum are expected to make significant and valuable contributions. Additionally, this cross-sectional study aimed to re-evaluate the three-level construct of OLF (Tugtekin, 2022a) amid the post-pandemic era, thus the variables of interest analyzed within the scope of the mentioned research are limited to the preferred variables. The epidemiological estimates and prevalence found in the study should be interpreted with caution. Finally, because of the cross-sectional nature of the current investigation, it is inappropriate to conclude the causality or directionality of detected associations.

4. Conclusion

Considering the conditions of our age and everchanging needs, online learning is growing relevance and focus on the higher education curricula, however, assessment techniques and instruments both for learners' and instructors' online learning fatigue levels are still limited in the educational technology and online learning literature. Additionally, various research conducted amid the COVID-19 pandemic reveals that attending an event online required more concentration than attending one in person (i.e., face-to-face) (de Oliveira Kubrusly Sobral et al., 2022). Another overlooked issue is that other video conferencing software is also susceptible to the same levels of fatigue brought on by online learning settings, which is described in the literature as "Zoom Fatigue" due to its ubiquitous use (de Oliveira Kubrusly Sobral et al., 2022; Peper et al., 2021). So, it does not matter which video conferencing platform is employed. Another striking finding of the current study is that females are more prone to be fatigued in online learning settings. This result is consistent with a survey-based study that revealed mirror anxiety to be a mediator of gender differences in online learning settings (Fauville et al., 2021) and a field experiment that demonstrated an increase in fatigue due to having a web camera, for females than for males (Shockley et al., 2021). There are various strategies to minimize fatigue levels, such as including silencing oneself, turning off the webcam, and refraining from staring at the mirrored video of the screen, according to the Attention Restoration Theory (Kaplan, 1995). Additionally, fully digital avatars can be used to obstruct video of the user in which females become more self-conscious and experience higher social anxiety (Ratan et al., 2022) and can help reduce negative self-focused attention while still allowing the user to self-monitor (Fauville et al., 2021). Therefore, this study also adds to the growing body of knowledge on online learning fatigue by verifying the effects of gender on fatigue. To effectively direct preventative efforts and implementations, it is essential to recognize and comprehend the factors that lead to high levels of fatigue. For scholars in educational technology and online learning, the significance of this subject should be addressed from a variety of angles. This cross-sectional study examined the levels of online learning fatigue in higher education and the structure of online learning fatigue for the post-pandemic period with robust statistical analyses, based on the adaptation of Lee et al. (2016)'s model designed to scrutinize the fatigue model from social networking services to online learning environments by Tugtekin (2022a). Furthermore, the 7-factor structure of the OLF construct was re-verified in the research for data from the post-pandemic era. Hence, OLF, which has adequate validity and reliability qualifications, may be used at all levels of higher education. The framework of the OLF construct developed and validated by Tugtekin (2022a) could be used by educational researchers, instructional designers, researchers in distance education, and instructors to assess the levels of online learning fatigue among students in higher education. Online learning researchers can also use the OLF to apply additional validation analyses or to scrutinize the roles played by distinct variables in online learning settings. On the other hand, interest in online learning environments is not limited just to academic, so it is crucial to consider the possibility that it may become ingrained in other professions or professional fields (Durak et al., 2020; Mays, 2021). This issue will continue to be significant in the future even if social distancing policies are progressively eased since hybrid and face-to-face meeting formats are expected to be embraced in many professional domains (Elbogen et al., 2022). In brief, the current study has the potential to make significant and multiplexed contributions to the determination of online learning fatigue levels in higher education, the development of preventive and improvement studies, and the advancement of research understanding and instructional innovations concerning online learning fatigue.

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