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In search of a measure to investigate cyberloafing in educational settings

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ABSTRACT

Cyberloafing is among the problematic tech-trends in contemporary work-based and educational settings. The current study administered an existing three-factor scale to three samples. The factor structure was not confirmed among high school teachers (n: 33), high school students (n: 479) and undergraduates (n: 86). A new and more comprehensive scale to address contemporary cyberloafing behaviors during lectures was developed through literature review, expert panels and observations. Data from undergraduate students (n: 471) were used for construct validation with an exploratory factor analysis (EFA), which revealed a five-factor structure and explained 70.44% of the total variance. Factors were sharing, shopping, real-time updating, accessing online content and gaming/gambling. The scale was administered to another undergraduate student sample (n: 215) and a social networker student group (n: 515). The structure was validated in these new samples through confirmatory factor analyses (CFA). The scale and current findings are expected to facilitate further cyberloafing research in educational settings.

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1. Introduction

Proliferation of internet technologies brought about many socio-psychological phenomena such as technology anxiety, Internet addiction and cyberbullying. Among these phenomena, intentional use of Internet access for personal purposes during work or lectures has become an issue of concern. Referred to as cyberslacking (Block, 2001; Greengard, 2000) or cyberloafing (Lim, 2002; Polito, 1997), this counterproductive use is one of the most common ways employees waste time at work (Weatherbee, 2010). Moreover, the density of cyberloafing is expected to trend upward due to constant advances in online connectivity opportunities and increasing availability of high-tech mobile devices.

Prevalence and predictors of cyberloafing in work-based settings have been documented well with empirical studies (Andreassen, Torsheim, & Pallesen, 2014; Garrett & Danziger, 2008; Sheikh, Atashgah, & Adibzadegan, 2015; Vitak, Crouse, & LaRose, 2011). While some scholars considered it as a counterproductive act which can cause economic loss (Block, 2001; Greengard, 2000) and reduced system performance due to excessive use of bandwidth (Sipior & Ward, 2002), others addressed its restorative and pleasurable consequences as well (Lim & Chen, 2009; Mastrangelo, Everton, & Jolton, 2006; Page, 2015). Recent work further investigated countermeasures to address cyberloafing such as blocking websites in the black list, providing reminder mechanisms to reduce misuse (Glassman, Prosch, & Shao, 2015), employing security systems to monitor Internet activity or enforcement of sanctions on those who caught cyberloafing (Ugrin & Pearson, 2013).

Though the issue has been primarily investigated in work-based settings, cyberloafing is catching attention from the field of education owing to massive technology integration investments and students' increasing access to digital technologies. Nevertheless, cyberloafing studies in educational settings are relatively novel. Online searches through relevant terms (i.e., cyberloafing, cyberslacking) reveal only a few studies in educational settings where university teachers (Zoghbi-Manrique-de-Lara, 2012), classroom teachers (McBride, Milligan, & Nichols, 2013), or in-service teacher training students (Page, 2015) are taken into consideration. That is, work-based settings are again the primary source of empirical data as observed in the previous literature.

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Recent studies began to evaluate the non-academic technology use of students in educational settings (Baturay & Toker, 2015; Karaoglan-Yılmaz, Yılmaz, Öztürk, Sezer, & Karademir, 2015; Taneja, Fiore, & Fischer, 2015). For instance, Baturay and Toker (2015) studied with 282 high school students to investigate the potential predictors of cyberloafing, which revealed that male, advanced and frequent users tend to cyberloaf more than female, novice and less frequent users. Similarly, Karaoglan-Yılmaz et al. (2015) studied with 288 freshman students, administered similar data collection tools and retained the findings regarding the predictive power of gender and Internet use frequency. In addition, the department was a significant predictor of cyberloafing. Finally, Taneja et al. (2015) administered a multifactor survey to 274 undergraduate students to investigate the factors influencing students' intentions to use technology for non-class related purposes. The structural equation model sheltered several predictors of cyberloafing attitudes such as consumerism, escapism, lack of attention, cyberloafing anxiety, and distraction by others' cyberloafing behavior. In addition, the role of motivation, engagement and course apathy on students' lack of attention was also explored. These studies either involved limited number of indicators within each factor (e.g., Taneja et al., 2015) or typical online behaviors addressed in previous scales (e.g., Baturay & Toker, 2015; Karaoglan-Yılmaz et al., 2015), whereas current affordances of social networking tools and mobile technologies are not adequately addressed through contemporary indicators.

Contemporary students or so-called digital natives are regarded intuitively as skillful multitaskers who can process multiple sources of information (Prensky, 2001; Veen & Vrakking, 2006). Nonetheless, this assumption is empirically challenged through a recent review (Kirschner & van Merrienböer, 2013). In addition, detrimental effects of multitasking on learning have been reported in different contexts such as mobile phone use and texting during leassons (Rosen, Lim, Carrier, & Cheever, 2008), laptop use (Sana, Weston, & Cepeda, 2013) and online messaging (Wang et al., 2012). A negative relationship with grades was also proposed (Junco & Cotten, 2012; Ravizza, Hambrick, & Fenn, 2014). Students may be switching between different sources of course-related information sequentially or they may be processing such information concurrently at the expense of effective learning. On the other hand, they may also be engaged in electronically-mediated activities that the instructor would consider non-academic such as tweeting and checking Facebook, both of which could be used for academic purposes as well (e.g., Aydin, 2012; Sharma, Joshi, & Sharma, 2016). As soon as students are allowed to use their laptops and mobile phones in the classroom, it is hard to differentiate between academic and non-academic online behaviors without tracking the mobile devices, which can be both unethical and illegal in some contexts. Furthermore, when the course content require students to use their mobile devices or the computer laboratory, the misuse may be indispensable.

In order to explore the nature and prevalence of such non-academic activities during lectures, reliable and valid scales to investigate the construct in educational settings are necessary. Majority of the previous frameworks and measures resorted to employees whereas students are not considered adequately. Moreover, some indicators which address cyberloafing in comfortable office environments (e.g., visiting adult websites) may not be applicable in school settings due to social desirability issues. In this regard, a frequently used cyberloafing scale was administered to different student and teacher populations to see its construct validity in educational settings. Upon unsuccessful validation of the scale with these samples, a new and more comprehensive scale was developed, exploratory and confirmatory analyses on different student samples were conducted, and the proposed factor structure was confirmed for educational contexts.

2. Theoretical background

2.1. Types of cyberloafing

Different types of cyberloafing have been proposed. One of the pioneering studies in the literature was conducted by Lim (2002), who classified cyberloafing as either a browsing or e-mailing activity. While the former included behaviors pertaining to how often individuals used the Internet to surf non-work sites (e.g., investment, news, sports, shopping), the latter involved checking, sending or receiving non-work related e-mails. The structure was quite useful at the time of scale development whereas current social networking technologies and accompanying online behaviors are not available in the scale.

Anandarajan, Devine, and Simmers (2004) examined personal web usage behaviors within two dimensions as 'opportunities versus threats' and 'organizational versus interpersonal'. Based on these two dimensions, personal web usage in the work-based settings was categorized as disruptive, recreational, personal learning and ambiguous use. The classification was useful as it addressed the underlying purpose of cyberloafing. However, the clusters were developed through respondents' perceptions about the appropriateness of a specific behavior rather than through investigating their actual behaviors (Blanchard & Henle, 2008).

Upon reviewing above classifications and relevant empirical work, Blanchard and Henle (2008) revisited the construct and surveyed 222 employed graduate business students. They identified two types of cyberloafing as minor and serious. While the former involved deviant acts like sending and receiving personal e-mails, visiting news or sports sites, online shopping and auctions; the latter involved misuse such as online gambling, surfing adult websites, participating in chat rooms, checking personals and reading blogs. Even though the classification was useful for further studies, differentiating between what is minor and what is serious may depend on the purpose of the action. That is, an employee may participate in chat rooms and read blogs for professional development which may not count as counterproductive for the organization.

Kalaycı (2010) tried to adapt the scale of Blanchard and Henle (2008) for educational settings through her dissertation. She resorted to responses of 205 Turkish undergraduate students. She eliminated non-adaptive items and proposed a new structure within three factors: personal works, socialization and news-reading. While the measure was easy to administer, its content validity was somewhat problematic due to elimination of many items from the original scale. In this regard, further studies in similar contexts employed modifications on the scale (e.g., Baturay & Toker, 2015; Karaoglan-Yılmaz et al., 2015).

In brief, there seems to be different types of cyberloafing which occur at different rates in different settings. Majority of these classifications were generated through resorting to employee data whereas student cyberloafing during lectures have been somewhat disregarded. Besides, these measures do not involve contemporary online behaviors that have become prevalent through constant advances in social networking tools. Thus, the prevalence and nature of the construct should be identified and examined through contemporary and plausible measures in educational contexts.

2.2. Explaining cyberloafing

Antecedents of cyberloafing have been explained through different perspectives. For instance, Lim (2002) resorted to the theoretical frameworks offered by social exchange, organizational justice and neutralization; and developed a model in which the primary source of cyberloafing was perceived justice. That is, when employees perceived their companies or coworkers to be unjust, they may engage in cyberloafing as a neutralization technique to restore justice.

Another perspective was proposed by Wagner, Barnes, Lim, and Ferris (2012) who resorted to the ego depletion model of self-regulation (Baumeister, Muraven, & Tice, 2000). The model posits that restraining impulses, sustaining self-control and volition depend on a common, limited, but renewable resource just like a muscle. This resource gets tired with use, but recovers with rest (Askew et al., 2014). In this regard, cyberloafing is considered as a way to recover self-control resources. Even though the theory was validated in different settings, it could not account for situations in which individuals conduct cyberloafing even when they are fully rested (Askew et al., 2014).

Recently, Askew et al. (2014) explained the cyberloafing construct through resorting to the theory of planned behavior (Ajzen & Fishbein, 1985). They considered several previous frameworks including the aforementioned perspectives and discussed their limitations. They considered antecedents of cyberloafing as subjective social norms, attitudes and perceived behavior control. These antecedents are mediated through intentions to engage in cyberloafing. The model was supported with both student and non-student employees in different empirical studies with explained variance values ranging from 32% through 37%.

Triandis' (1977) theory of interpersonal behavior was tested by Moody and Siponen (2013) to extend the arguments of the theory of planned behavior and explain non-work-related personal use of the Internet at work. Attitudes, social influence and intentions were already proposed constructs by the theory of planned behavior. The new perspective delved further into constructs such as emotional factors, habits and different sources of social influence. The model was tested with 238 employees at a Finnish company with a non-work-related Internet use policy where the majority of research hypotheses were empirically supported.

Further studies resorted to similar theoretical frameworks and investigated the antecedents of cyberloafing such as employee job attitudes and organizational characteristics (Liberman, Seidman, McKenna, & Buffardi, 2011); personality, satisfaction, and perceived performance (O'Neill, Hambley, & Bercovich, 2014); engagement and personality traits (O'Neill, Hambley, & Chatellier, 2014); self-control and organizational justice (Restubog et al., 2011); coping with work routine and intensification (Page, 2015); or new sets of variables to explain cyberloafing attitudes (Taneja et al., 2015).

To sum up, several theoretical frameworks have been embraced to explain the nature and predictors of cyberloafing in different settings. The studies mostly focused on work-based settings rather than educational environments. To measure cyberloafing, some scholars resorted to previous two-factor structures (e.g., Liberman et al., 2011; Restubog et al., 2011), some adapted or developed very short questionnaires with limited number of items (e.g., O'Neill, Hambley, & Bercovich, 2014, O'Neill, Hambley, & Chatellier, 2014; Taneja et al., 2015), and some provided limited information regarding the construct validity of the scale (e.g., Page, 2015). Thus, the current study aimed to test whether a previous measure, which was adapted from work-based settings (Kalaycı, 2010), worked effectively in educational contexts to investigate cyberloafing. Then, a new set of items was proposed along with an up-to-date factor structure, which addressed cyberloafing through adding recent online networking behaviors.

3. Material and methods

The current work was designed as a four-phase research study. The first phase involved the administration of a previous cyberloafing scale to three different samples to investigate its construct validity and suitability for the current educational context. The second phase resorted to scale development steps identified by DeVellis (2012) to investigate the prevalence of contemporary cyberloafing behaviors among students. The third and fourth phases were realized to confirm the suggested factor structure with undergraduate and social networker students successively.

Survey methodology was followed throughout the study. In addition, observations, expert panels and literature review were used to generate a new item pool during the scale development phase. Finally, the fourth phase, which recruited participants through a Facebook game, was deliberately involved as a confirmation step, since recent evidence revealed that face-to-face and online implementation of self-report measures may result in different findings (Denniston et al., 2010; Payne & Barnfather, 2012).

3.1. Participants

Quantitative data were collected seven times in the current study in which Turkish participants in different educational settings were recruited. Three of these were realized in the first phase with 33 high school teachers, 479 high school students and 86 undergraduates who were accessed through convenience sampling. For the second phase, which involved scale development and construct validation through an exploratory factor analysis (EFA), data were collected from 471 undergraduate students from four randomly selected colleges of education across the country. The third phase involved 215 undergraduate students from another randomly selected college of education, which was not included in previous phases. The final phase of the study involved purposeful sampling, which was conducted with 515 Facebook users who reported to be an active student during the time of data collection. Demographics are summarized in Table 1.

3.2. Measures

In the first phase of the study, the cyberloafing scale adapted by Kalaycı (2010) was used. The original instrument was developed for work-based settings by Blanchard and Henle (2008). Kalaycı (2010) eliminated non-adaptive items and proposed a 13-item structure within three factors: personal works, socialization and news-reading. Respondents used a five-point scale to indicate the frequency of engagement in cyberloafing through 1 (never) to 5 (a great extent). Following an expert panel with five scholars in related fields, the comprehensiveness of the scale and fit values in different confirmatory analyses led the authors to question the suitability of the scale for school settings (see Table 2). Thus, in further phases of the study, a new scale was developed and confirmed through administrations in different settings.

The purpose of the new scale was to determine the degree of cyberloafing during lectures. Scale development steps proposed by DeVellis (2012) were particularly helpful. First of all, items that reflected cyberloafing during lectures were generated through a literature review (e.g., Blanchard & Henle, 2008; Lim, 2002), expert opinions, observations in IT classes and interviews with students at a state college of education. The item format was determined as a Likert scale similar to previous studies. Responses regarding the frequency of cyberloafing ranged from 1 (never) to 5 (a great extent). To minimize self-selection bias, similar studies were followed (Juvonen & Gross, 2008), and the term 'cyberloafing' was not used in either scale instructions or items. The initial 52-item form was reviewed by six reviewers who had international publications on instructional technology and scale development. They rated how relevant they thought each item was to the measured construct. They further commented on the clarity and conciseness of the items. Similar items were not eliminated at the inception

Table 1
Participants.

Research phase	Female		Male	
	f	%	*f*	%
Phase 1 – Administration of the previous scale with high school teachers (n: 33)	24	72.7	9	27.3
Phase 1 – Administration of the previous scale with high school students (n: 479)	260	54.3	219	45.7
Phase 1 – Administration of the previous scale with undergraduate students (n: 86)	39	45.3	47	54.7
Phase 2 – EFA with the new scale (undergraduates, n: 471)	278	59	193	41
Phase 3 – Confirmation with undergraduate students (n: 215)	143	65.9	72	33.2
Phase 4 – Confirmation with social networker students (n: 515)	24	4.7	491	95.3

Table 2
Summary of the confirmatory factor analyses conducted on the previous scale.

Fit criteria	Kalaycı (2010)	Teachers	High school students	Undergraduates	Acceptable	Rationale
Sample size	100	33[a]	479	86	item*5	Kass and Tinsley (1979)
					item*10	Kline (2011)
					100	Tanaka, Panter, Winborne, and Huba (1990)
$\chi 2$/df	106.24/62 = 1.71	42.87/24 = 1.79	338.63/24 = 14.11[a]	57.53/24 = 2.4	2.5	Kline (2011)
					3	Sümer (2000)
RMSEA	0.059	0.157[a]	0.166[a]	0.128[a]	0.08	Hooper et al. (2008)
SRMR	0.076	0.079	0.062	0.059	0.10	Worthington and Whittaker (2006)
NNFI	0.98	0.88[a]	0.93	0.92	0.90	Schumacker and Lomax (1996)
CFI	0.98	0.92	0.95	0.94	0.90	Hu and Bentler (1999)
GFI	0.93[a]	0.77[a]	0.86[a]	0.87[a]	0.90	Hooper et al. (2008)
AGFI	0.89[a]	0.57[a]	0.74[a]	0.75[a]	0.90	Schumacker and Lomax (1996)

[a] Beyond ideal values.

and their relative effectiveness was evaluated during the pilot administration. The final form included 49 items which was administered to 24 undergraduate students to determine response time and improve reader-friendliness.

3.3. Data collection

Except for the last phase of the study, paper–and–pencil administration was realized. Institutional review board consents were obtained for each university before scale administrations. Besides, to see whether the construct validity of the scale was retained during web administration, the last phase resorted to a popular game on Facebook. On the game homepage, users who reported to be an active student at the time of data collection were directed to the survey page. The completion of the questionnaire was awarded with bonus points in the game. The data collection process was completed in April 2015.

3.4. Data analysis

Data were processed through exploratory (EFA) and confirmatory factor analyses (CFA). After relevant fit indices were reported, descriptive statistics and internal consistency coefficients (alpha) were calculated for each factor. Relationships among factors were investigated through correlation coefficients, whereas factor means were compared with each other through one-way within-groups ANOVA. To realize gender comparisons independent-samples t-tests were conducted. Effect size indices were reported for statistically significant findings.

4. Results

4.1. Phase 1 – administration of the previous scale

The scale of Kalaycı (2010), which was adapted to Turkish from Blanchard and Henle (2008) was evaluated through an expert panel in order to address its comprehensiveness and suitability for contemporary online behaviors observed in educational settings. Expert ratings were mostly below average and their comments guided researchers to develop further items. Yet, its construct validity was tested.

The data from high school teachers, high school students and undergraduate students were processed through confirmatory factor analyses in LISREL 9.1. Analyses are summarized in Table 2. While reporting the findings in CFAs, the model chi square, RMSEA, CFI and SRMR were considered necessary (Worthington & Whittaker, 2006). Further fit values were also included. The model chi-square/df ratio in the high school population was not regarded as a serious deviation from an acceptable model, since this statistic can be quite sensitive to sample size and rejects the models when large samples are used (Kline, 2011). Similarly, GFI is quite sensitive to the number of parameters and sample size which has led scholars to question its usability (Hooper, Coughlan, & Mullen, 2008; Sharma, Mukherjee, Kumar, & Dillon, 2005). However, RMSEA is one of the most informative fit indices in model evaluations (Diamantopoulos & Siguaw, 2000). Even though a liberal cutoff was chosen to evaluate the suitability of RMSEA (i.e., 0.08), values were unacceptable in all samples. Thus, in addition to the comprehensiveness of the scale adapted by Kalaycı (2010), its fit values were found problematic, which urged researchers to develop the new scale.

4.2. Phase 2 – EFA with the new scale

In order to see how many constructs underlie the new set of items, principal-components analysis with Varimax rotation was conducted through IBM SPSS Statistics 23. Several criteria were considered to check the suitability of the dataset for factor analysis such as the sample size ($n > 300$) and item intercorrelations (Tabachnick & Fidell, 2007). When all participants are drawn from a single population who share certain characteristics, factor stability and generalizability may be effected even with large-enough samples (Worthington & Whittaker, 2006). In this regard, the developmental sample for the current EFA, which was drawn from four different colleges of education, was considered plausible.

In terms of the suitability of the sizes of the correlations in the matrix, two statistical measures were checked. First of all, Bartlett's Test of Sphericity was significant ($p < 0.001$). However, this test is susceptible to the influence of large sample sizes. More specifically, in studies with cases-per-item ratios higher than 5:1, researchers may need to provide additional evidence of scale factorability (Worthington & Whittaker, 2006). Thus, the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was used as a second measure. The KMO value was 0.921, which was far above the minimum value of 0.6 for a good factor analysis (Tabachnick & Fidell, 2007).

The analysis was realized through an expert panel of three scholars so that item deletion and retention decisions were found plausible through multiple perspectives. Similar to the factorability decisions mentioned above, multiple criteria for factor retention were considered. In addition to usual eigenvalue checks for factorability such as Kaiser Criterion (Kaiser, 1958) and the scree plot illustrated in Fig. 1 (Cattell, 1966), parallel analysis was implemented (Hayton, Allen, & Scarpello, 2004). These procedures revealed five factors.

The main criteria for item deletion was the elimination of items with loadings less than 0.32 or cross-loadings less than 0.15 difference from an item's highest loading (Worthington & Whittaker, 2006). If there were two or more indicators measuring the same construct, those with lower communalities, lower corrected-item total correlations and lower factor loadings were eliminated. To decide the final shape of the factor structure, the number of items per factor (≥ 3) and the conceptual interpretability of the structure were considered (Worthington & Whittaker, 2006). The final solution included 30 items under five factors: Sharing, shopping, real-time updating, accessing online content and gaming/gambling. The solution explained 70.44% of the variance, which was far better than the observed variance values in the literature (Henson & Roberts, 2006).

The internal consistency coefficients of all factors were plausible (DeVellis, 2012; Pallant, 2011). The coefficient for the whole scale was 0.942. Item loadings ranged between 0.49 through 0.92. According to Comrey and Lee (1992), almost all items were either excellent (i.e., above 0.71) or very good (i.e., above 0.63) in terms of factor loadings. Descriptive statistics regarding factors and items are provided in Table 3.

Factors were related with each other as summarized in Table 4, which can facilitate multivariate analyses in further research. They also revealed acceptable skewness and kurtosis values (Table 5), which meant that the factor means were normally distributed (George & Mallery, 2010). That is, factor means can be used as dependent variables in further parametric analyses. A repeated-measures ANOVA with the Bonferroni Correction revealed that except for the difference between sharing and accessing online content, all means were significantly different from each other (Wilk's Lambda: 0.339; $F_{4,467} = 227.635$; $p < 0.001$; partial eta squared:0.661). That is, sharing and accessing online content had the highest means, followed by real-time updating, shopping and gaming/gambling successively. Males and females did not differ in terms of sharing ($t_{469} = -0.706$; $p = 0.48$), real-time updating ($t_{469} = 0.366$; $p = 0.71$) and accessing online content ($t_{469} = -1.452$; $p = 0.15$), whereas males outperformed females in terms of online shopping ($t_{469} = -4.873$; $p < 0.001$; eta squared: 0.048) and gaming/gambling ($t_{469} = -13.020$; $p < 0.001$; eta squared: 0.265). In brief, there were different types of cyberloafing which occurred at different rates.

4.3. Phase 3 – confirmation with undergraduate students

To see whether the proposed factor structure was confirmed in a different undergraduate sample, another CFA was conducted

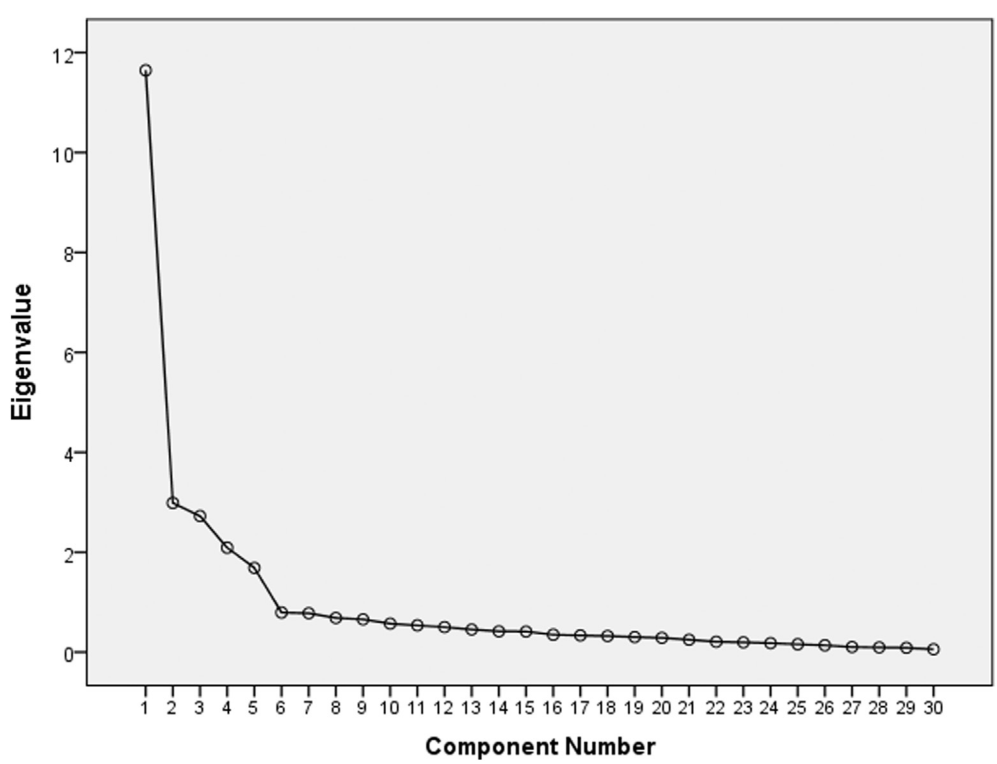

Fig. 1. Scree plot of the exploratory factor analysis.

Table 3
Summary of the exploratory factor analysis.

Factors and items	Eigenvalues	Explained variance	Mean	SD	Item total r	Factor load
Factor 1 – Sharing (Alpha: 0.933)			*3.52*	*0.94*		
I check my friends' posts	11.7	38.82	3.81	1.04	0.79	0.81
I check my friends' social networking profiles			3.54	1.16	0.79	0.81
I share content on social networks (photo, video, etc.)			3.49	1.22	0.84	0.80
I like posts that are interesting			3.78	1.09	0.78	0.77
I comment on shared photos			2.96	1.14	0.74	0.77
I post status updates on social networks			3.48	1.24	0.77	0.74
I tag friends on photos			2.87	1.24	0.71	0.71
I chat with friends			4.07	1.06	0.66	0.67
I watch shared videos			3.68	1.21	0.71	0.66
Factor 2 – Shopping (Alpha: 0.875)			*2.51*	*1.03*		
I shop online	2.99	9.96	2.63	1.41	0.75	0.80
I visit deal-of-the-day websites			2.00	1.25	0.61	0.71
I visit online shopping sites			3.03	1.33	0.67	0.71
I visit auction sites			2.48	1.36	0.66	0.70
I use online banking services			2.52	1.50	0.64	0.67
I visit online shops for used products			2.62	1.39	0.65	0.65
I check job advertisements			2.31	1.29	0.60	0.62
Factor 3 – Real-time updating (Alpha: 0.941)			*2.81*	*1.31*		
I retweet a tweet I like	2.72	9.08	2.87	1.53	0.92	0.92
I favorite a tweet I like			2.84	1.51	0.91	0.91
I post tweets			2.88	1.49	0.91	0.90
I read tweets			3.19	1.49	0.85	0.87
I comment on trending topics			2.28	1.27	0.62	0.64
Factor 4 – Accessing online content (Alpha: 0.938)			*3.60*	*1.32*		
I download music	2.09	6.97	3.49	1.54	0.89	0.83
I watch videos online			3.83	1.37	0.85	0.82
I listen to music online			3.63	1.53	0.86	0.82
I download videos			3.37	1.54	0.85	0.78
I download applications I need			3.67	1.37	0.71	0.67
Factor 5 – Gaming/Gambling (Alpha: 0.814)			*2.20*	*1.13*		
I visit betting sites	1.69	5.62	1.87	1.35	0.79	0.92
I bet online			1.75	1.28	0.76	0.89
I check online sport sites			2.74	1.54	0.59	0.73
I play online games			2.46	1.44	0.45	0.49

Total variance: 70.443%; KMO: 0.921; Bartlett's Test of Sphericity $p < 0.001$.

Table 4
Correlations among scale factors.

Variables	Phase	Shopping	Real-time updating	Accessing online content	Gaming/gambling
Sharing	2	0.462[a]	0.439[a]	0.578[a]	0.318[a]
	3	0.431[a]	0.422[a]	0.726[a]	0.292[a]
	4	0.387[a]	0.320[a]	0.492[a]	0.284[a]
Shopping	2		0.366[a]	0.582[a]	0.429[a]
	3		0.337[a]	0.519[a]	0.487[a]
	4		0.367[a]	0.197[a]	0.426[a]
Real-time updating	2			0.419[a]	0.220[a]
	3			0.293[a]	0.284[a]
	4			0.151[a]	0.356[a]
Accessing online content	2				0.350[a]
	3				0.364[a]
	4				0.253[a]

[a] All correlation coefficients are significant at the p-value of 0.001.

Table 5
Skewness and kurtosis values in each administration.

Phase	Phase 2 – EFA with undergraduates				Phase 3 – CFA with undergraduates				Phase 4 – CFA with social networker students			
Index	Skewness		Kurtosis		Skewness		Kurtosis		Skewness		Kurtosis	
Factor	Statistic	Std. error	Statistic	Std. error	Statistic	Std. error	Statistic	Std. error	Statistic	Std. error	Statistic	Std. error
Sharing	−0.66	0.11	0.25	0.22	−0.34	0.17	−0.50	0.33	−0.16	0.11	−0.03	0.21
Shopping	0.28	0.11	−0.74	0.22	1.22	0.17	0.76	0.33	0.36	0.11	−0.72	0.21
Real-time updating	0.05	0.11	−1.30	0.22	1.05	0.17	−0.17	0.33	0.35	0.11	−1.16	0.21
Accessing online content	−0.72	0.11	−0.81	0.22	−0.71	0.17	−0.66	0.33	−0.60	0.11	−0.11	0.21
Gaming/gambling	0.90	0.11	−0.15	0.22	2.05	0.17	4.31	0.33	0.33	0.11	−0.48	0.21

Values between −2 and +2 are considered acceptable (George & Mallery, 2010).

Table 6
Evaluation of the new CFAs.

Fit criteria	Phase 3Undergraduates	Phase 4Social networker students	Acceptable	Rationale
Sample size	215	515	item*5	Kass and Tinsley (1979)
			item*10	Kline (2011)
			100	Tanaka et al. (1990)
χ^2/d	912.59/395 = 2.31	1667.93/395 = 4.22[a]	2.5	Kline (2011)
			3	Sümer (2000)
RMSEA	0.078	0.079	0.08	Hooper et al. (2008)
SRMR	0.096	0.093	0.10	Worthington and Whittaker (2006)
NNFI	0.96	0.93	0.90	Schumacker and Lomax (1996)
CFI	0.96	0.93	0.90	Hu and Bentler (1999)
GFI	0.77[a]	0.79[a]	0.90	Hooper et al. (2008)
AGFI	0.74[a]	0.76[a]	0.90	Schumacker and Lomax (1996)

[a] Beyond ideal values.

with 215 undergraduate students. Neither modification indices nor item parceling was implemented so that fit values pertaining to the original structure could be revealed. Summary and evaluation of the CFA is provided in Table 6. Except for the GFI values, which have been questioned due to their sensitivity to the number of parameters and the sample size (Sharma et al., 2005), all fit indices were acceptable before conducting any modification on the original model. The total variance explained by the model was 67.05%. All factors had ideal internal consistency coefficients. Descriptive statistics, standardized coefficients, t values and errors are provided in Table 7.

Similar to the dataset in the scale development study, all factors were related with each other and normally distributed except for the slight leptokurtic distribution in the gaming factor (Table 5). This deviance could be eliminated through a non-linear transformation. Thus, it can easily meet the assumptions of further parametric tests. A repeated-measures ANOVA with the Bonferroni Correction revealed that except for the difference between shopping and real-time updating, all means were significantly different from each other (Wilk's Lambda: 0.272; $F_{4,213} = 142.393$; $p < 0.001$; partial eta squared:0.728). Accessing online content had the highest mean, followed by sharing, shopping and real-time updating, and gaming/gambling. Similar to the previous analyses, males and females did not differ in terms of sharing ($t_{213} = -0.153$; $p = 0.88$), real-time updating ($t_{213} = -0.959$; $p = 0.34$) and accessing online content ($t_{213} = -1.728$; $p = 0.09$), whereas males outperformed females in terms of online shopping ($t_{213} = -6.141$; $p < 0.001$; eta squared: 0.15) and gaming/gambling ($t_{213} = -9.454$; $p < 0.001$; eta

Table 7
Summary of the confirmatory factor analysis with undergraduate students.

Factors and items	Mean	SD	Factor load	t value	Error
Factor 1 – Sharing (Alpha: 0.926)	*2.96*	*0.97*			
I check my friends' posts	3.36	1.18	0.76	12.90	0.43
I check my friends' social networking profiles	2.83	1.18	0.78	13.35	0.40
I share content on social networks (photo, video, etc.)	2.80	1.24	0.84	15.01	0.30
I like posts that are interesting	3.31	1.29	0.80	13.83	0.37
I comment on shared photos	2.34	1.06	0.79	13.73	0.37
I post status updates on social networks	2.49	1.19	0.79	13.68	0.38
I tag friends on photos	2.47	1.26	0.71	11.87	0.49
I chat with friends	3.82	1.11	0.70	11.59	0.51
I watch shared videos	3.21	1.38	0.72	12.02	0.48
Factor 2 – Shopping (Alpha: 0.87)	*1.82*	*0.88*			
I shop online	1.88	1.25	0.79	13.37	0.38
I visit deal-of-the-day websites	1.61	1.01	0.68	10.93	0.53
I visit online shopping sites	2.34	1.33	0.75	12.50	0.43
I visit auction sites	1.88	1.16	0.80	13.63	0.36
I use online banking services	1.80	1.21	0.66	10.56	0.56
I visit online shops for used products	1.63	1.11	0.69	11.08	0.52
I check job advertisements	1.58	1.01	0.49	7.28	0.76
Factor 3 – Real-time updating (Alpha: 0.928)	*1.91*	*1.14*			
I retweet a tweet I like	1.87	1.28	0.91	17.30	0.17
I favorite a tweet I like	2.13	1.41	0.92	17.56	0.16
I post tweets	1.93	1.34	0.95	18.73	0.10
I read tweets	1.88	1.32	0.92	17.82	0.15
I comment on trending topics	1.71	1.05	0.54	8.53	0.70
Factor 4 – Accessing online content (Alpha: 0.944)	*3.43*	*1.29*			
I download music	3.44	1.40	0.89	16.62	0.21
I watch videos online	3.47	1.39	0.95	18.49	0.11
I listen to music online	3.49	1.46	0.89	16.64	0.21
I download videos	3.05	1.46	0.81	14.45	0.34
I download applications I need	3.67	1.39	0.82	14.69	0.32
Factor 5 – Gaming/Gambling (Alpha: 0.796)	*1.58*	*0.86*			
I visit betting sites	1.32	0.90	0.92	16.50	0.16
I bet online	1.22	0.70	0.89	15.79	0.21
I check online sport sites	1.94	1.34	0.52	7.90	0.73
I play online games	1.83	1.25	0.62	9.90	0.61

Chi-Square = 912.59, df = 395, RMSEA = 0.078.

squared: 0.296). Similar to the previous analysis, different types of cyberloafing occurred at different rates in this sample as well.

4.4. Phase 4 – confirmation with social networker students

The current factor structure was developed and confirmed in face-to-face settings. To see whether it was also valid during web administrations, another CFA was conducted with 515 social networker students. Similar to the previous CFA, no modification or item parceling was conducted. Summary and evaluation of the CFA is provided in Table 6. Except for the GFI values discussed above, fit values were acceptable. Chi square/df ratio was beyond the ideal value due to very large sample size (Kline, 2011). The explained variance was ideal (i.e., 52.31%), but weaker than the previous confirmation. Descriptive statistics pertaining to items and factors are provided in Table 8. The last item had a slightly weaker but statistically significant t value, and it revealed a high error covariance. This was due to the nature of the data collection context, which was an online gaming environment.

Previous analyses were repeated in the current dataset, which revealed interrelated (Table 4) and normally distributed factors (Table 5). A repeated-measures ANOVA with the Bonferroni Correction revealed that except for the difference between shopping and real-time updating, all means were significantly different from each other (Wilk's Lambda: 0.434; $F_{4,511} = 166.414$; $p < 0.001$; partial eta squared:0.566). Accessing online content had the highest mean, followed by sharing, gaming/gambling, shopping and real-time updating. Male averages were higher than that of females in terms of gaming/gambling ($t_{513} = -2.858$; $p < 0.01$; eta squared: 0.016), whereas they did not differ with regard to sharing ($t_{513} = -0.067$; $p = 0.95$), shopping ($t_{513} = -0.294$; $p = 0.77$), real-time updating ($t_{513} = 1.116$; $p = 0.27$) and accessing online content ($t_{513} = -0.723$; $p = 0.47$). That is, the online implementation validated the factor structure, and supported the previous argument that cyberloafing had different types which occurred at different rates.

5. Discussion and conclusion

5.1. Theoretical and practical implications

In the current study, we introduced and validated a five-factor cyberloafing scale which was consistent across different student populations. In addition, each cyberloafing behavior occurred at different rates across samples as observed in the previous work (Lim, 2002). These findings retained the arguments of Blanchard and Henle (2008) that there are different types of cyberloafing and each form may have different antecedents. Studying with the current and updated factor structure may help researchers to investigate antecedents of each type effectively so that organizations and educational administrators can develop appropriate policies and sanctions to address each cyberloafing form.

Previous research suggested that males engaged in significantly more frequent personal Internet use than females (e.g., Garrett & Danziger, 2008). This difference was particularly observed in terms of leisure-related surfing rather than non-work-related Internet communication. The current study revealed a similar pattern with regard to gender, but a different outcome with regard to the cyberloafing type and the context of data collection. More specifically, the average of males was higher in terms of online shopping and gaming in face-to-face administrations while other cyberloafing types were similar across genders. However, the pattern changed in online administration where males outperformed females only in terms of gaming/gambling. This suggested that gender was a significant predictor of particular cyberloafing forms, but this prediction changed with regard to the type of cyberloafing and the nature of the target population.

Further investigation of the items in each construct revealed that two of the factors particularly involved items pertaining to current and popular social networking tools. More specifically, *sharing* involved items pertaining to Facebook behaviors whereas *real-time updating* was particularly about Twitter. The high occurrence rate of these factors in all administrations suggested that previous factor structures (e.g., browsing & e-mailing) might not be adequate anymore to address the types and prevalence of contemporary cyberloafing behaviors. Aside from Facebook and Twitter activities, the current factor structure included shopping, gaming and downloading behaviors, which may serve effectively in future studies as well.

5.2. Limitations and future research directions

The current study addressed cyberloafing indicators pertaining to current and popular information technology tools, and involved them in a reliable measure to explore the construct. Constant developments in online networking technologies should be taken into account to develop new and appropriate indicators in future research so that empirical studies can explain a higher amount of variance in the target variable of cyberloafing.

Current factors revealed acceptable normal distribution indices, which can be used in further studies to realize parametric and higher-order tests. In addition, since the factors were statistically and theoretically related, multivariate analyses of variance are applicable in further research. Affordances of web surveys can also be utilized in further research since the factor structure was validated through a web survey as well. Explained variance values were above average in all administrations (Henson & Roberts, 2006). Yet, trying to unveil the unexplained variance through new indicators and across new populations is suggested.

The current samples were limited to Turkish undergraduate and social networker students. Validation studies across different fields of study and cultures are needed to explore the nature and prevalence of cyberloafing among students. Besides, concurrent and discriminant validity studies may be needed to understand the nature of the construct and its relationship with relevant background variables. While the nature and types of cyberloafing were explored, its reasons and detrimental effects were not within the scope of the current scale development study. In this regard, course-related and personal antecedents of cyberloafing in educational settings may be investigated through exploratory studies. In addition, experimental multitasking studies can be conducted to understand the degree of its detrimental effects on learning activities. Finally, development of new items will be necessary in accordance with the contemporary developments in online communication technologies.

5.3. Concluding remarks

Advances in online connectivity provide us with novel opportunities to extend learning beyond the boundaries of the classrooms. Empirical studies highlight the educational affordances of contemporary social networking sites such as Twitter (e.g., Gao, Luo, & Zhang, 2012; Junco, Heiberger, & Loken, 2011) and Facebook (e.g., Aydin, 2012; Sharma et al., 2016). While these tools may reduce anxiety and increase engagement in instructional contexts through providing new interaction opportunities, they may also be used for non-academic purposes. Since concurrent multitasking in class can interfere with instructional effectiveness, documenting the prevalence and predictors of cyberloafing in educational settings seem relevant. In this regard, integrating the current measure into empirical studies to diagnose the extent, predictors and covariates

Table 8
Summary of the confirmatory factor analysis with social networker students.

Factors and items	Mean	SD	Factor load	t value	Error
Factor 1 – Sharing (*Alpha: 0.852*)	*3.35*	*0.76*			
I check my friends' posts	3.47	1.08	0.65	15.73	0.58
I check my friends' social networking profiles	3.19	1.10	0.67	16.47	0.54
I share content on social networks (photo, video, etc.)	3.20	1.17	0.77	19.60	0.41
I like posts that are interesting	3.76	1.05	0.62	14.92	0.61
I comment on shared photos	2.83	1.12	0.59	14.02	0.65
I post status updates on social networks	3.05	1.17	0.70	17.38	0.51
I tag friends on photos	2.91	1.26	0.56	13.06	0.69
I chat with friends	3.90	1.08	0.53	12.29	0.72
I watch shared videos	3.86	1.08	0.55	12.83	0.70
Factor 2 – Shopping (*Alpha: 0.869*)	*2.47*	*1.01*			
I shop online	2.47	1.34	0.77	19.92	0.41
I visit deal-of-the-day websites	2.10	1.28	0.73	18.37	0.47
I visit online shopping sites	2.72	1.35	0.79	20.82	0.37
I visit auction sites	2.50	1.38	0.78	20.26	0.39
I use online banking services	2.47	1.41	0.64	15.43	0.59
I visit online shops for used products	2.73	1.36	0.61	14.48	0.63
I check job advertisements	2.29	1.32	0.56	13.24	0.68
Factor 3 – Real-time updating (*Alpha: 0.928*)	*2.43*	*1.29*			
I retweet a tweet I like	2.42	1.48	0.90	26.31	0.19
I favorite a tweet I like	2.70	1.55	0.86	24.37	0.26
I post tweets	2.43	1.46	0.94	28.36	0.11
I read tweets	2.46	1.47	0.91	26.93	0.16
I comment on trending topics	2.15	1.35	0.67	16.86	0.56
Factor 4 – Accessing online content (*Alpha: 0.867*)	*3.73*	*0.97*			
I download music	3.56	1.27	0.71	17.86	0.50
I watch videos online	3.97	1.10	0.87	24.01	0.24
I listen to music online	4.03	1.09	0.88	24.45	0.23
I download videos	3.32	1.36	0.66	16.10	0.57
I download applications I need	3.78	1.15	0.69	17.23	0.52
Factor 5 – Gaming/Gambling (*Alpha: 0.727*)	*2.83*	*1.00*			
I visit betting sites	2.33	1.38	0.93	25.18	0.14
I bet online	2.25	1.39	0.92	24.93	0.15
I check online sport sites	3.03	1.39	0.49	11.52	0.76
I play online games	3.69	1.22	0.19	4.17	0.96

Chi-Square = 1667.93, df = 395, RMSEA = 0.079.

of cyberloafing may help us study the construct effectively. Moreover, there seems to be a potential relationship between the development of digital literacy skills, opportunities to access high-tech mobile devices and the prevalence of cyberloafing. Thus, the current study may have implications for both educational settings and other organizations which try to integrate the most recent online connectivity tools and digital skills to their unique contexts.

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