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Online Homework Distraction Scale: A Validation Study

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Abstract

Background: Increasingly, postsecondary students enroll in distance learning courses and complete homework online, which extends their learning opportunities regardless of where they are. Online homework requires self-control from students to cope with conventional and tech-related distractors, however research on this topic is scarce. There is a need to develop an instrument to assess online homework distractions in higher education. **Method:** This study examined the psychometric properties of the Online Homework Distraction Scale (OHDS) based on 612 undergraduates in China. After randomly dividing the sample into two groups, we carried out a principal component analysis (PCA) with one group and confirmatory factor analysis (CFA) with another group. **Results:** Both PCA and CFA findings indicated that tech-related distraction and conventional distraction were empirically indistinguishable for college students. Given acceptable measurement invariance, the latent factor mean was examined over gender for all participants and found that men were more distracted while doing online homework. Concerning validity evidence, in line with theoretical predictions, the OHDS was negatively related to online homework expectancy, value, effort, and time management. **Conclusions:** Our study provides strong evidence that the OHDS is a valid and reliable instrument for measuring online homework distraction.

Keywords: Online homework; distraction; new media technology; online learning; self-regulation; undergraduate.

Resumen

Online Homework Distraction Scale: un Estudio de Validación. **Antecedentes:** el aprendizaje online requiere del autocontrol para hacer frente a los distractores convencionales y los relacionados con las nuevas tecnologías. En la Educación Superior, existe la necesidad de desarrollar un instrumento para evaluar los distractores a la hora de realizar las tareas para casa en modo online. **Método:** el estudio examinó las propiedades psicométricas de la Online Homework Distraction Scale (OHDS). Participaron 612 estudiantes universitarios de China. La muestra fue dividida aleatoriamente en dos grupos. Se realizó Análisis de Componentes Principales (ACP) con un grupo y Análisis Factorial Confirmatorio (AFC) con el otro grupo. **Resultados:** los resultados del ACP y del AFC indicaron que la distracción relacionada con la tecnología y la distracción convencional eran empíricamente indistinguibles. Constatada una invariancia de medida aceptable, se examinó la media del factor latente sobre el género para todos los participantes. Los hombres se distraen más que las mujeres mientras realizan las tareas online. Con respecto a la evidencia de validez, el OHDS se relacionó negativamente con la expectativa, el valor, el esfuerzo y la gestión del tiempo. **Conclusiones:** hay evidencia sólida de que el OHDS es un instrumento válido y fiable para medir el nivel de distracción en tareas online.

Palabras clave: tareas de casa online; distracción; nuevos medios tecnológicos; aprendizaje online; alumnos universitarios.

Distractions are hard to avoid while engaging in achievement-related activities (Schmitz & Wiese, 2006; Wolters, 2011). It becomes more of a challenge for students to follow through their homework assignments in the midst of more appealing activities during after-school hours (e.g., phone call, TV, and conversations with family members) with less structure and time constraints than classwork (Cooper et al., 2006; Xu, 2015).

Recently, the advent of new media technology (e.g., smartphones, laptops, and tablets) has posed a new challenge for students when doing their homework (Bowman et al., 2010; David et al., 2014; Xu, 2015). The use of nonacademic electronic media (e.g., texting) while doing homework and attending classes has a negative impact on studying experiences, homework completion, and GPA (Flanigan & Babchuk, 2015; Junco & Cotton, 2011).

One theoretical framework concerning distraction is dual attentional processes (Corbetta et al., 2008; Corbetta & Shulman, 2002), including (a) goal-driven (top-down) attention in which the brain voluntarily sets to focus on the target activity, and (b) stimulus-driven (bottom-up) attention in which the brain is redirected by external stimuli. Because of the brain's physical limitations, our attentional capacities are limited. Hence, distributing attention between different activities can hinder and interfere with student learning and performance (Kahneman, 1973; Pashler et al., 2001).

Stimulus-driven attention can be influenced by the properties of external stimuli (e.g., text messaging) and the target activity (e.g., working on homework assignments; Bowman et al., 2010; Kahneman, 1973; Hillstrom & Chai, 2006; Pashler et al., 2001). A number of researchers (e.g., Corbetta & Shulman, 2002; Pashler et al., 2001) postulated that external stimuli with characteristics of being novel, salient, or changeable are more apt to pull attention away from the target activity, especially if it is considered as uninteresting and requires mental effort. Hence, in comparison

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with conventional distraction (e.g., daydreaming and background conversation), tech-related distraction may represent a different kind of distraction, because of novelty, visual arousal, and seamless invasion of work, play, and social interaction (e.g., "wired for distraction" and "right at my fingertips"; Bowman et al., 2010; Flanigan & Babchuk, 2015).

It is surprising, however, that little research has examined whether conventional distraction and new media technology related distraction (i.e., tech-related) are empirically distinguishable. Two rare exceptions are one validation study with middle school students (Xu et al., 2016) and another validation study with high school students (Xu, 2015). Based on 1,799 students in grades 10-11, Xu (2015) conducted a confirmatory factor analysis (CFA) to examine whether tech-related distraction and conventional distraction were empirically distinguishable for high school students. Results revealed that, compared with one-factor model (CFI = .874; SRMR = .050; RMSEA = .159; 90% CI [.146 - .172]), the two-factor model yielded a significantly better fit (CFI = .983; SRMR = .020; RMSEA = .062; 90% CI [.048 - .077]). Thus, technology-related distraction and conventional distraction were empirically distinct for these high school students.

Similarly, based on 796 students in grade 8, Xu et al. (2016) conducted CFA to investigate whether tech-related distraction and conventional distraction were empirically distinguishable for middle school students. Results indicated that, compared with one-factor model (CFI = .855; SRMR = .072; RMSEA = .123; 90% CI [.104 - .143]), the two-factor model resulted in a significantly better fit (CFI = .970; SRMR = .034; RMSEA = .060; 90% CI [.039 - .083]). Thus, technology-related distraction and conventional distraction were empirically distinct for these middle school students. Although these results are interesting and extend prior research in the field, they are limited to secondary school students, in the context of traditional homework.

Recent, an increasing number of postsecondary students have taken distance education courses. For instance, the amount of students enrolling at least one distance course reached to 6.4 million in US in 2016, representing 31.6% of the all students (Seaman et al., 2018). Indeed, the movement towards distance education is evident in other populated countries (e.g., India & China; Trehan et al., 2017). Consequently, a growing number of college students have been required to complete homework in online settings (Khanlarian & Singh, 2015; Zhou et al., 2017). In fact, a recent systematic review showed that online homework is majorly investigated in higher education (Magalhães et al., 2020).

With increasingly more advanced technological devices at their disposal, students work on online homework almost anywhere and anytime. At the same time, they are exposed to various tech-related distraction (e.g., texting and online games; Bowman et al., 2014; Zhou et al., 2017). To follow through and complete online homework, "online learners are required to be acquainted with skills to prevent themselves from numerous attractions of online multimedia or entertainment" (Tsai, 2009, p. 40). Along the same line, they are required to take more initiatives to exercise self-control and cope with tech-related distraction (Yushau & Khan, 2014). Thus, over time, online college students may become more accustomed to new media technology and more skillful in dealing with tech-related distraction (Zhou et al., 2017), thereby less likely to consider new media technology as novel or visual stimulating (compared with secondary students in the context of traditional homework). Therefore, it would be intriguing to investigate whether tech-related distraction and conventional distraction are distinguishable in the context of online homework.

Whereas Xu et al. (2016) found that factor loadings were across gender for middle school students, Xu (2015) did not test gender invariance for high school students. Hence, it would be important to investigate gender difference in online homework distraction for college students for the following reasons. First, as students move from high school to college, a majority of them have changed their study habits, with homework in particular. For example, one student in the study by Furst et al. (2018) stated: "I am definitely more focused now than I was in high school because I am in college at this point. I have to take it more serious because I pay for school" (p. 54). Similarly, another student noted:

I usually find a specific time to do my homework, a specific place to do it and just be a little more responsible than I was a few years ago. Because I want to pass this class so I can take the class I need to take, and you know from there get a degree, so I can get a job, get a lot of money and be happy (p. 55).

In addition, other studies found that college females take their academic work more seriously in the technologically rich environment (e.g., mobile phones; Hanson et al., 2011), and they tend to use more versatile strategies to regulate their attention in the face of the increase of social medial use (Wu & Cheng, 2019).

The aim of the current investigation is to assess the psychometric properties of Online Homework Distraction Scale (OHDS) for college students concerning online homework. The specific purposes are: (a) to examine the OHDS' factor structure, by conducting a principal component analysis (PCA) with one half of the sample and confirmatory factor analysis (CFA) with the second half of the sample; (b) to test its invariance over gender; (c) to assess its reliability (Cronbach's alpha and omega coefficients); and (d) to assess its validity evidence in terms of its relationship to online homework expectancy, value, effort, and time management. As expectancy and value positively influence on task engagement and persistence (Eccles & Wigfield, 2002), it is hypothesized that the OHDS is negatively associated with expectancy and value. Furthermore, as volitional control and self-regulatory resource management strategies (e.g., effort and time management) play an important role in guarding against distraction in achievement-related activities (Boekaerts & Corno, 2005; Corno, 2004), and as distraction adversely affects task completion (Junco & Cotten, 2011; Xu, 2015), it is hypothesized that the OHDS is negatively related to online homework effort, and time management.

Method

Participants

Six hundred and twelve college students (74.5% females; 67.5% part-time students; 100% Han Nationality) participated in the current investigation. Participants came from a number of majors from one university in southeastern China, including accounting, business administration, computer science, economics, education, human resource administration, and psychology.

Approaching half were juniors (44.3%), whereas the rest were about evenly divided among freshmen, sophomores, and seniors (18% to 19%). The age breakdown for the undergraduates in the current investigation was 2.1% aged 18 or under, 40.5% aged 19-24, 32.4% aged 25-29, 7.5% aged 30-34, and 4.6% aged 35 or above. Overall, 17.5% were not employed, 43.5% were part-time employees, and 39.0% were full-time employees.

Procedure

The present study was a part of a broader investigation to examine a number of topics regarding online homework (e.g., value, expectancy, and teacher involvement in online homework). Several trained research assistants administrated the instrument (discussed below) in regular online sessions. Participants were told that the purpose of the study was to learn more about how they view online homework. They were asked to focus on their responses regarding their online homework assignments in one required online course in their majors.

Instruments

OHDS. The OHDS contains six items from studies validated with middle and high school students (Xu, 2015; Xu et al., 2016). As displayed in Table 1, these distractions consist of: (a) conventional distraction, from daydream to watching TV while working on online homework assignments; and (b) tech-related distraction, from stopping online homework assignments to send text messages to playing games. All six items employed 5-point ratings, including 1 (*never*), 2 (*rarely*), 3 (*sometimes*), 4 (*often*), or 5 (*routinely*). These items were formatted in a positive direction to reduce the likelihood of response bias (Suárez-Alvarez et al., 2018).

We asked several homework experts from US and China to check the appropriateness of homework distraction items for undergraduates in online learning settings. In addition, we held a joint meeting with university administrators and faculty members to seek their perspectives on these items. Based on these inputs, the only adaptation made for the present investigation is that we used "online assignments," instead of "math homework" (as in the case with middle and high school students; Xu, 2015; Xu et al., 2016). For our investigation, the correlations among these six items varied from .59 to .82, and its alpha coefficient was .93.

Online Homework Expectancy and Value. We assessed online homework expectancy and value using the Homework Expectancy Value Scale (HEVS; Xu et al., 2019), which contains two subscales – expectancy and value. Four items measured participants' expectancy belief regarding online homework (e.g., self-confidence to follow through and complete online assignments; α = .87). Four items assessed participants' value belief regarding online homework (e.g., the importance of online homework; α = .86). All eight items in HEVS included 4-point ratings, from 1 (*strongly disagree*) to 4 (*strongly agree*).

Online homework effort. Four items assessed participants' online homework effort, informed by related previous studies (Flunger et al., 2017; Xu, 2018). These items tapped into students' initiatives to follow through and complete online homework assignments (e.g., "I always try to finish my online assignments"; α = .71). Ratings for items in this scale varied from 1 (*strongly disagree*) to 4 (*strongly agree*).

Online homework time management. Based on time management in online learning environments (Xu et al., 2013) and time management with traditional homework (Xu et al., 2014), this scale contained six items to assess student initiatives to plan and regulate time spent on online homework (e.g., setting priorities to meet homework deadlines; α = .86). Ratings for item in this scale varied from 1 (*never*) to 5 (*routinely*).

Data analysis

The data was analyzed in several phases, coinciding with the objectives of the study. First, to examine the OHDS' factor structure, participants were randomly divided into two groups (i.e., Group 1, *n* = 306; Group 2, *n* = 306). With Group 1, we conducted a principal component analysis (PCA) using SPSS version 25.0 with direct oblimin rotation (delta = 0) to determine if items could be reduced into broader components (Calderón-Garrido et al., 2019). Our justification for using direct oblimin rotation is that tech-related distraction and conventional distraction were found to be related for secondary school students (e.g., Xu et al., 2016). Our decision for retaining factors was determined by a number of methods such as eigenvalues, scree plots, and conceptual meaningfulness of each item on each factor. With Group 2, we conducted CFA using Mplus version 7.2 to examine whether tech-related distraction and conventional distraction were empirically distinguishable by comparing the difference in goodness-of-fit between (a) one-factor model (factorially indistinct) and (b) two-factor model (factorially distinct).

Second, to test its invariance over gender, we performed a multi-sample analysis in Mplus version 7.2 applying robust maximum likelihood estimation with robust standard errors. It consisted of configural invariance (baseline model), factor loading invariance (placing equality constraints on the factor loadings), and intercept invariance (placing equality constraints on the intercepts).

Third, to assess its reliability**,** alpha coefficient and omega coefficient were used to assess OHDS' reliability. We used the criteria of $\alpha \geq .70$ to assess the adequacy of alpha coefficient for research purpose (Nunnally, 1978). Additionally, we followed the commendation that the adequacy of omega coefficient need to meet the same criteria as alpha coefficient (Watkins, 2017).

Table 1
Descriptive Statistics and Standardized Coefficients for the One-Factor CFA Model

Construct	Items	Skewness	Kurtosis	Mean	SD	β
Distraction	Daydream while doing online assignments	0.942	0.394	2.09	1.08	.752
	Start conversations unrelated to what I am doing	0.630	0.255	2.32	0.98	.798
	Stop online assignments to watch my favorite TV show	0.978	0.729	2.00	0.98	.876
	Stop online assignments to play video games	1.133	0.850	1.88	0.99	.907
	Stop online assignments to send or receive email	0.841	0.400	2.08	1.00	.896
	Stop online assignments to send or receive text messages	0.578	0.152	2.32	1.00	.871

Note: Group 2. *N* = 306. Composite reliability (CR) = .940. Average variance extracted (AVE) = .723

Fourth, to assess its validity evidence in terms of its relationship to online homework expectancy, value, effort, and time management, we examined Pearson correlations between the OHDS and these four external measures.

Fifth, for the evaluation of the models, multiple goodness-of-fit indicators were used, including CFI ≥ .95 (Hu & Bentler, 1999), TLI ≥ .95 (Hu & Bentler, 1999), RMSEA < .08 (MacCallum et al., 1996), and SRMR < .08 (Hu & Bentler, 1999). Additionally, we used the Akaike information criterion (AIC) to compare alternative models as it takes into account both the goodness-of-fit and the number of parameters (Bentler, 1995). Although there are no guidelines for the AIC, smaller values indicate better fit (Hu & Bentler, 1999). Because of the issue related to the chi-square test, we used the criteria of ΔCFI < .01 and ΔRMSEA < .015 (Chen, 2007; Cheung & Rensvold, 2002) for testing gender invariance.

In the current investigation, missing values for the 6-item OHDS ranged from 8.17% to 9.15% (M = 8.80%), and they were imputed using the expectation-maximization.

Results

OHDS' Structural Validity

For Group 1 (n = 306), the Kaiser-Meyer-Olkin measure was appropriate for PCA (.898). PCA findings revealed a one-factor model, which was upheld using parallel analysis based on randomly generated datasets (306 participants × 6 items). The one-factor model explained 73.1% of the total variance. All six items loaded heavily (ranging from .790 to .903) on the single factor that could be labeled as online homework distraction, thereby suggesting that tech-related distraction and conventional distraction were empirically indistinguishable for Group 1.

For Group 2 (n = 306), as shown in Table 2, CFA results indicated that the one-factor model yielded an adequate fit ($MLR\chi^2$ = 20.676; df = 9; CFI = .984; TLI = .973; RMSEA = .065; 90% CI [.028 - .102]; SRMR = .017; AIC = 3783.594). CFA results further revealed that the two-factor model did not result in a better fit ($MLR\chi^2$ = 21.975; df = 8; CFI = .980; TLI = .962; RMSEA = .076; 90% CI [.039 - .114]; SRMR =.022; AIC = 3891.302) than did the one-factor model. Therefore, tech-related distraction and conventional distraction were empirically indistinguishable for Group 2. As presented in Table 1, the standardized estimates were substantively meaningful (ranging from .752 to .907), thus lending additional support to its convergent validity (Maruyama, 1998).

Gender Invariance

Regarding the one-factor model, gender invariance was examined for the entire sample (n = 612). As presented in Table 3, the configural invariance showed acceptable fit to the data ($MLR\chi^2$ = 56.188; df = 18; CFI = .972; TLI = .954; RMSEA = .083; 90% CI [.059 - .108]; SRMR = .023). Subsequently, we tested factor loading invariance ($MLR\chi^2$ = 67.380; df = 23; CFI = .968; TLI = .958; RMSEA = .079; 90% CI [.058 - .102]; SRMR = .035). Factor loadings was invariant over gender (*Δ*CFI = .004; ΔRMESA < .004). We then examined intercept invariance ($MLR\chi^2$ = 81.503; df = 28; CFI = .961; TLI = .959; RMSEA = .079; 90% CI [.059 - .099]; SRMR = .037). Hence, intercept was invariant over females and males (*Δ*CFI = .007; ΔRMESA < .001).

Given acceptable measurement invariance across gender, we compared the latent factor mean across gender. Because the mean of a latent variable could not be estimated directly (Hancock, 1997), females served as the reference group. Findings revealed that males had a significantly higher mean than females by .473 (z = 5.497; p < .001). Cohen's (1988) d effect size index was calculated, in which the latent mean difference was divided by the pooled standard deviation over groups (Hong et al., 2003). The calculated value of d was 0.537 between these groups, which can be defined as medium according to Cohen's guidelines.

OHDS' Reliability

With respect to descriptive statistics, the mean for the OHDS was 2.09 (SD = 0.88). Its alpha coefficient was .93, and the corresponding omega coefficient was .93. These reliability coefficients are typically viewed as excellent in measurement literature (Nunnally, 1978; Watkins, 2017). Item-total correlations for the OHDS varied from .718 to .857, indicating good homogeneity.

Table 2
Model Comparison: Summary of Goodness-of-Fit Indices

Models	$MLR\chi^2$	df	CFI	TLI	RMSEA	RMSEA 90% CI	SRMR	AIC
1. One-factor model	20.676	9	.984	.973	.065	.028 - .102	.017	3783.594
2. Two-factor model	21.975	8	.980	.962	.076	.039 - .114	.022	3891.302

Notes: Group 2. N = 306

Table 3
Gender Invariance: Summary of Goodness-of-Fit Indices

	Invariance models	$MLR\chi^2$	df	CFI	TLI	RMSEA	RMSEA 90% CI	SRMR	Model Comparison	ΔCFI	ΔRMSEA
1	Configural	56.188	18	.972	.954	.083	.059 - .108	.023	–	–	–
2	Factor loading	67.380	23	.968	.958	.079	.058 - .102	.035	2 vs. 1	.004	.004
3	Intercept	81.503	28	.961	.959	.079	.059 - .099	.037	3 vs. 2	.007	< .001

Notes: N = 612

OHDS' Validity Evidence

Concerning the OHDS' validity evidence, we examined Pearson correlations between the OHDS and four theoretically relevant external measures. In line with the hypotheses, the OHDS was negatively related to online homework expectancy (r = -.503, p < .001), online homework value (r = -.438, p < .001), online homework effort (r = -.155, p < .001), and online homework time management (r = -.112, p < .001).

Discussion

The aim of the present study is to evaluate the psychometric properties of the OHDS. Where appropriate, the recommendations offered by Muñiz and Fonseca-Pedrero (2019) were followed. Our study contributed to the literature on online learning by revealing that tech-related distraction and conventional distraction were empirically indistinguishable for undergraduates in the context of online homework, and by revealing that the OHDS exhibited excellent reliability (both Cronbach's alpha and omega coefficients). While in line with prior literature on online learning and distraction (Tsai, 2009; Yushau & Khan, 2014; Zhou et al., 2017), these findings further suggest that undergraduates become more skillful and adaptive to new media technology related distraction in the online homework process, thereby no longer considering tech-related distraction as a distinct form of distraction.

In addition, our results concerning intercept invariance suggest that the OHDS is equally valid with females and males. Furthermore, consistent with related literature that females take academics work more seriously and use more versatile strategies to regulate attention when using new media technology (Hanson et al., 2011; Wu & Cheng, 2019), our study takes another step forward, by revealing that males (compared with females) are more distracted while doing online homework (with medium effect size). Finally, consistent with theoretical predications (Boekaerts & Corno, 2005; Corno, 2004; Eccles & Wigfield, 2002; Junco & Cotten, 2011; Xu, 2015), the OHDS was negatively related to online homework expectancy, value, effort, and time management. Taken together, the OHDS appears to have good psychometric properties (structural validity, reliability, and validity evidence), representing a valid means for assessing online homework distraction for undergraduates.

Our findings regarding the OHDS ought to be useful to researchers and online instructors who are interested in and concerned with homework distraction in online learning environments. In fact, this can be one of the factors that may explain fewer positive results of online homework (when compared to traditional homework) on students' homework engagement and academic performance (Magalhães et al., 2020). Researchers may find the OHDS useful to examine the relations between homework distraction and other variables such as homework quality, expectancy, value, effort, online learning strategies, and completion in online learning environments (Núñez et al., 2015; Rosário et al., 2018; Tsai, 2009), particularly as our study suggests that the OHDS is applicable across gender.

Online instructors may apply the OHDS to have a better idea of students' distraction, thus providing relevant support and feedback to help them to deal with distraction while doing online assignments (e.g., by making online homework more purposeful and by incorporating relevant learning strategy instruction into online classes). Furthermore, given our finding that tech-related distraction and conventional distraction were not empirically distinguishable, it would be important to help online learners to cope with conventional distraction (e.g., daydreaming and watching TV) and tech-related distraction (e.g., texting and playing online games), particularly as our study indicated that online homework distraction was negatively associated with online homework effort and time management. In addition, given our finding that males were more vulnerable to online homework distraction than females, it would be beneficial to pay close attention to males in the online homework process (e.g., homework value and feedback). Finally, the OHDS provides online students with a diagnostic tool for better understanding and self-monitoring their online homework behaviors.

Concerning further research, given most of the participants were women, there is a need to replicate the present findings with a representative sample of online students, particularly in cross-cultural settings. First, this is the first study that we are aware of that adopted a multifaceted approach to evaluate psychometric properties of the OHDS for undergraduates concerning their online homework assignments. Second, cultural differences may shape student distraction in achievement-related activities (e.g., cultural differences concerning the importance of effort, concentration, and persistence; Rao et al., 2000; Xu, 2015). In addition, it would be highly desirable to compare our present findings concerning online homework with relevant findings concerning traditional homework with college students. Another important line of research is to focus on those online students with higher scores on the OHDS to help them deal with online homework distraction (e.g., using self-regulatory strategies), then examining its impact on subsequent online homework completion, performance, and academic learning.

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