Transactions on Replication Research

Methodological Replication DOI: 10.17705/1atrr.00059 ISSN 2473-3458

Exhaustion from Information System Career Experience: Are the Implications for Turn-Away Intention Different for Millennials?

Michael A. Erskine
Jones College of Business
Middle Tennessee State University
michael.erskine@mtsu.edu

Sam Zaza
Jones College of Business
Middle Tennessee State University
sam.zaza@mtsu.edu

Stoney Brooks
Jones College of Business
Middle Tennessee State University
stoney.brooks@mtsu.edu

Scott J. Seipel
Jones College of Business
Middle Tennessee State University
scott.seipel@mtsu.edu

Abstract:

As evidence suggests that exhaustion is particularly pronounced in Millennials, we investigate if generational differences affect the drivers of information systems (IS) career turn-away intention (TAI). An indication of such differences would be of importance toward retaining professionals in the IS workforce as Millennials will soon become the largest generation in the U.S. workforce. To elucidate such differences, this paper presents a methodological replication of "Exhaustion from Information System Career Experience: Implications for Turn-Away Intention" by Armstrong, Brooks, and Riemenschneider (2015). While we did not determine significant generational differences, our findings contrast from the original study. Specifically, we found support for the impact of exhaustion from IS career experience on TAI, while an evaluation of resources no longer influences career-level exhaustion.

Keywords: IS personnel, workforce, millennial generation, burnout, exhaustion, affective commitment, turn-away intention, occupational turnover

The manuscript was received 11/15/2019 and was with the authors 4 months for 3 revisions.

1 Introduction

The IT sector is increasingly concerned about the supply of qualified IT professionals to fill positions. It is estimated that the global technology sector will experience a deficit of more than 1.1 million qualified professionals in 2020, increasing to a deficit of 4.3 million by the year 2030 (Korn Ferry, 2018). The economic cost of these shortages is estimated to be USD 449.7 billion in unrealized revenue globally. Accordingly, not being able to retain talented IT professionals may hinder the U.S. in sustaining its position as the global leader in technology. The U.S. Bureau of Labor Statistics[1] projects that employment in the computer and information technology occupations will grow by 12 percent from 2018 through 2028, adding about 546,200 new jobs. Several studies have addressed job turnover and career turn-away to help managers, organizations, educational institutions, and policymakers make informed decisions regarding the IT workforce.

Moreover, some IS researchers have shown that exhaustion, one dimension of burnout, is related to turnover intention (TOI) (e.g., Ahuja et al., 2007) and turn-away intention (TAI) (e.g., Armstrong et al., 2015). While TOI is an IT professional's intention to leave the *organizatio*n, TAI represents an intention to leave the IS *profession*. Thus, a better understanding of burnout and its effect on TAI could help organizations develop strategies to reduce such intentions and behaviors.

Burnout has been conceptualized into three dimensions: exhaustion, depersonalization, and reduced personal accomplishment (Lee & Ashforth, 1996; Wright & Cropanzano, 1998). More recently, taking into consideration the changing nature of IT functions, depersonalization and reduced personal accomplishments were substituted with cynicism and professional efficacy (Leiter & Maslach, 2016). Being exhausted is the most apparent symptom of burnout (Maslach et al., 2001, p. 402) and, therefore, is considered the initial signal of the burnout process (Maslach & Schaufeli 1993). Exhaustion conceptualizes an individual's "feelings of being emotionally overextended and depleted" (Maslach, 1998, p. 69).

The popular press (Petersen, 2019; Sanghani, 2019) and academic literature (George & Wallio, 2017; Jiang et al., 2017; Lu & Gursoy, 2016; Worly et al., 2019) have argued that the effects of burnout acutely impact Millennials (defined as individuals born between 1981-1996[2]). For instance, 96% of Millennials indicate that burnout affects their everyday life (Yellowbrick, 2019), and 72% of these respondents indicate that work was the primary cause of the burnout. These statistics are alarming. Such perceptions could be attributed to recent workplace changes (e.g., virtual teams, remote work) or unrealistic performance expectations resulting from the continued unfulfilled demand for IT professionals. However, no clear empirical data exist to explain these perceptions. As Millennials will soon be the largest generation in the U.S. workforce (Bialik & Fry, 2019), the issue of burnout and its impact on career turn-away intention has become a greater concern for industry and research.

Generational differences are challenging to capture as they are predominantly formed through collective experiences shared during the formative years (Ryder, 1985). Thus, definitions of generations applied in the United States may not work in other contexts (Mannheim, 1970). However, studies have frequently shown that generational differences exist and influence empirical research (e.g., Schullery, 2013; Singh 2013).

The topics of TOI and TAI are of importance to IS research and practice, as findings directly impact the development and implementation of programs to sustain and grow the IT workforce. As research in these areas often informs policy decisions (e.g., Kim, 2012), it is crucial to ensure a scientific consensus of findings. Validating findings and expanding theory through replication studies allows such consensus to develop. Replication studies provide a defensible test of empirical research and ensure that initial studies did not detect significant relationships due to unknown influences (Cronbach, 1957; Smith, 1970). Dennis and Valacich (2014) identify three distinct replication research approaches: exact, conceptual, and methodological. Exact replications follow the original study methodology and context. Conceptual replications may add new measurement items or constructs. A methodological approach replicates the original methodology but in a different context (Olbrich et al., 2017).

To confirm the original findings, we conduct a methodological replication of Armstrong et al. (2015). Moreover, we plan to follow their exact methodology but apply stratified sampling to ensure significant samples to detect generational differences. The next section presents the research model developed by

[1] https://www.bls.gov/ooh/computer-and-information-technology/home.htm
[2] https://www.pewresearch.org/fact-tank/2019/01/17/where-millennials-end-and-generation-z-begins/

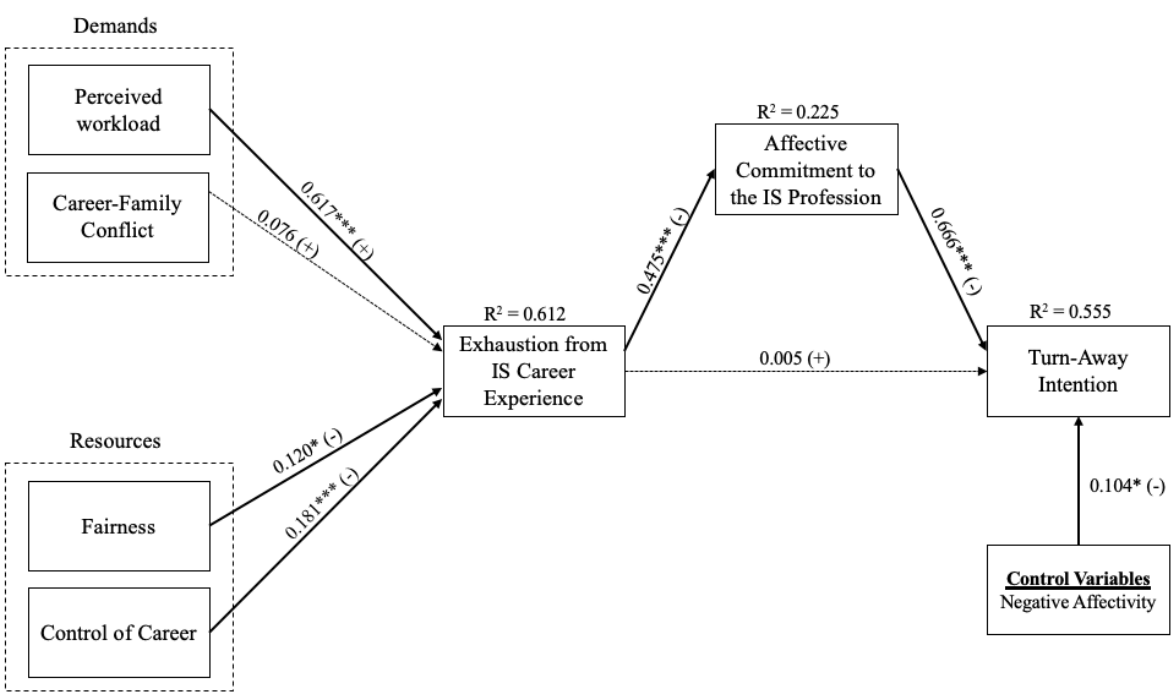
Armstrong et al. (2015). This section is followed by an outline of the data collection methods, and analyses applied. Following this section, we present our results. After this, we discuss and compare our findings to those of Armstrong et al. (2015). Finally, we emphasize the limitations of this study and provide suggestions for future research directions.

2 Research Hypotheses

Bringing the model developed by Ahuja et al. (2007) to the career level, Armstrong et al. (2015) adopted the Job Demand-Resources (JD-R) framework to structure the antecedents of exhaustion. To capture TAI, the job- or role-level constructs were mapped to the career level. The eight hypotheses posited in the original study are shown in Table 1, and the findings are shown in Figure 1. Their theoretical model included constructs of TAI, exhaustion from IS career experience (EISCE), affective commitment to the IS profession (ACISP), perceived workload, career-family conflict (CFC), perceived fairness, and perceived control of career across the IS career experience (ISCE). Furthermore, their model was controlled for negative affectivity (NA).

Table 1. Hypotheses Developed by Armstrong et al. (2015)

Hypothesis
H_1: EISCE will positively influence TAI.
H_2: EISCE will negatively influence ACISP.
H_3: ACISP will negatively influence TAI.
H_4: ACISP will mediate the EISCE-TAI relationship.
H_5: Perceived workload across ISCE will positively influence EISCE.
H_6: Perceived CFC across ISCE will positively influence EISCE.
H_7: Perceived fairness across ISCE will negatively influence EISCE.
H_8: Perceived control of career across ISCE will negatively influence EISCE.



Notes:
1) The numbers in the path model represent β; * p < 0.05; ** p < 0.01; *** p < 0.001.
2) Bold, solid paths are significant.
3) Dashed paths are nonsignificant.

Figure 1. Armstrong et al. (2015) Final Model Paths

Based on qualitative data, Armstrong et al. (2015) recognized the need to look at the career experience rather than at a specific job to predict TAI. They argued that IT professionals who feel exhausted from their IS career experience are more likely to leave the IS profession to alleviate that feeling and ultimately less likely to be committed to the IS career. Also, IT professionals are more likely to feel exhausted if they perceive a higher workload across their IS career or feel a conflict between their career and family obligations. Alternately, IT professionals are more likely to feel less exhausted from their IS career experience when outcomes received across their IS career experience are perceived as fair, or they perceive greater control over adjusting their career based on their needs, abilities, and circumstances.

The findings from Armstrong et al. (2015) identified the importance of mapping the job level related constructs, specifically exhaustion, to the career level (e.g., EISCE) to better predict TAI. For instance, the authors found that fairness transcends job boundaries and career experience, and signals to management the need to implement procedures that are perceived as fair if they want to retain valued IT professionals. Armstrong et al. (2015) called for universities and professional entities to communicate what the real expectations and experiences of an IS career would entail.

Using a methodological replication, we distill whether these empirical findings differ between Gen Xers (defined as individuals born between 1965 and 1980[3]) and Millennials.

3 Replication Method

For this methodological replication, we adopt the methodological steps followed in the original study. A contextual difference is that we specifically examine the model on Gen Xers and Millennials. Assessing generational differences should provide a more specific context for the understanding of TAI. Furthermore, we performed stratified sampling to ensure that we had mostly equal groups of Gen Xers and Millennials. To determine the minimum required sample size for the two groups, we performed a G-power analysis. Based on a variety of factors, G-power performs a statistical power analysis to determine minimum sample sizes to reject the null hypothesis and therefore achieve statistically significant results when testing the model (Cohen, 1988). The G-Power recommended sample size was 134 for each subject group to reject the null hypothesis at an 80% level of power (Cohen, 1988). We sought a sufficiently larger sample for each generation with at least 250 subjects per group.

Armstrong et al. (2015) suggest that by contacting the CIOs of organizations to encourage participation in their study, response bias may have been a factor. Thus, we purposefully sought samples from a wide variety of organizations without executive involvement. Accordingly, we recruited our sample using Qualtrics Panels, which ensured that all subjects met the necessary study attributes. This criteria-based sampling method was used to select respondents having the attributes of interest for conducting our study (Creswell, 2013). Management and IS literature have successfully used this type of sampling for the same reason as ours (e.g., Carlson et al., 2012; Ferguson et al., 2012; Moquin et al., 2019). This method also provided a more representative sample of the current IT workforce[4], as the original study sample included mostly white subjects (93.5%) who work in the South-Central United States.

Table 2 provides a comparison of our sample demographics compared to the original study.

Table 2. Sample Demographics

	Original Study (N=293)	**Replication Study (N=512)**
Gender		
Male	*58.0%*	*61.9%*
Female	*42.0%*	*37.9%*
Missing/No Answer	-	*0.2%*

[3] https://www.pewresearch.org/fact-tank/2019/01/17/where-millennials-end-and-generation-z-begins/
[4] Using data collected in 2014, the United States Equal Employment Opportunity Commission reported high-tech industry demographics as: 68.53% White, 7.40% Black, 7.94% Hispanic, and 14.04% Asian American. See https://www.eeoc.gov/eeoc/statistics/reports/hightech/ for the full report.

Table 2. Sample Demographics

Generation		
Millennial	-	50.8% (n=260)
Generation X	-	49.2% (n=252)
Ethnicity		
White	*93.5%*	*63.7%*
African American	*4.4%*	*15.6%*
Hispanic	*0.3%*	*8.8%*
Asian	-	*10.4%*
Other	*1.7%*	*1.6%*
Education		
High school or less	-	*4.7%*
Some College	*14.0%*	*6.3%*
Associate Degree	*10.9%*	*11.3%*
Undergraduate Degree	*60.8%*	*49.6%*
Master's Degree	*13.7%*	*28.1%*
Missing	*5.8%*	-
Marital Status		
Never Married	*12.3%*	*26.6%*
Married/Living with Partner	*72.0%*	*62.3%*
Separated/Divorced	*11.3%*	*9.0%*
Widowed	*1.0%*	*2.1%*
Missing	*3.4%*	-
Industry		
Transportation	*36.6%*	*2.1%*
IT Services/Software	*27.0%*	*66.2%*
Healthcare	*17.1%*	*4.5%*
Other	*10.8%*	*24.4%*
Government	*6.8%*	*2.7%*
Missing	*1.7%*	-
Position		
Software Developer	*33.9%*	*9.2%*
IS/IT Director or Manager	*11.3%*	*57.2%*
Project Manager or Lead	*11.3%*	*9.0%*
Technical Support Staff	*11.0%*	*12.1%*
Business or Systems Analyst	*9.6%*	*5.7%*
Database Administrator	*6.3%*	*4.1%*
Other	*15.9%*	*2.7%*
Missing	*0.7%*	-
Tenure in the IS Profession		
Mean	*14.4*	*12.1*
Standard Deviation	*9.3*	*6.6*
Notes: 1) While the original study reported age ranges, it did not report generational differences. However, based on definitions of generations, the original sample included mostly Gen Xers and some Baby Boomers.		

All measurement items were identical to those used by Armstrong et al. (2015). Additionally, the control items of the original study, including age, tenure in the IS field, gender, and negative affectivity were maintained. Responses were collected online using Qualtrics XM.

While a total of 518 subjects agreed to participate, the data cleansing resulted in a final sample of N=512. Subsequently, descriptive statistics were reported using IBM SPSS 26. Next, the research model was analyzed using partial least squares structural equation modeling (PLS-SEM) using SmartPLS 3.2.9 (Ringle, Wende, & Becker, 2015). Finally, to compare the groups, a permutation procedure was conducted (Chin & Dibbern, 2010).

4 Findings

Consistent with the original study, we evaluated the measurement and structural model. As we seek to explore generational differences, we analyzed the model on each group independently, as well as combined.

To evaluate the measurement model, construct reliability, convergent validity, and discriminant validity were examined. Construct reliability was established as all Cronbach's alpha, and composite reliability values were higher than the recommended threshold of 0.7 (Hair et al., 2017; Nunnally & Bernstein, 1994). Convergent validity was established by ensuring that items loaded highest on the appropriate construct. Additionally, the Average Variance Extracted (AVE) for each construct was above the .5 minimum threshold established by Fornell and Larcker (1981). Table 3 shows the convergent validity and construct reliabilities for the Armstrong et al. (2015) study findings (S_1), the replication study with Gen Xer sample findings (S_2), and the replication study with Millennial sample findings (S_3).

Table 3. Convergent Validity and Construct Reliabilities

Construct	AVE			Cronbach's α			Composite Reliability		
	S_1	S_2	S_3	S_1	S_2	S_3	S_1	S_2	S_3
ACISP	0.650	0.689	0.656	0.865	0.722	0.735	0.903	0.869	0.851
CFC	0.853	0.853	0.818	0.943	0.944	0.926	0.956	0.959	0.947
CTRL	0.671	0.717	0.520	0.878	0.902	0.745	0.911	0.926	0.834
EISCE	0.828	0.802	0.784	0.931	0.918	0.908	0.951	0.942	0.935
FAIR	0.676	0.697	0.587	0.881	0.889	0.833	0.912	0.919	0.876
PW	0.714	0.765	0.769	0.866	0.898	0.900	0.909	0.929	0.930
TAI	0.744	0.851	0.846	0.886	0.913	0.909	0.921	0.945	0.943

Notes:
1) ACISP = Affective Commitment to the IS Profession; CFC = Career–Family Conflict; CTRL = Control of Career; EISCE = Exhaustion from IS Career Experience; FAIR = Fairness; PW = Perceived Workload; TAI = Turn-Away Intention
2) Armstrong et al. (2015) study findings = S_1; replication study with Gen Xer sample findings = S_2; replication study with Millennial sample findings = S_3

Next, as suggested by Fornell and Larcker (1981), the square root of each construct's AVE was calculated to establish discriminant validity. See Table 4 for the results of this analysis.

Table 4. Construct Correlations

Construct	Study	ACISP	CFC	CTRL	EISCE	FAIR	PW	TAI
ACISP	S_1	**0.806**						
	S_2	**0.830**						

Table 4. Construct Correlations

	S_3	**0.810**						
CFC	S_1	-0.198	**0.924**					
	S_2	-0.441	**0.924**					
	S_3	-0.509	**0.905**					
CTRL	S_1	0.308	-0.126	**0.819**				
	S_2	0.104	-0.075	**0.847**				
	S_3	0.204	-0.160	**0.721**				
EISCE	S_1	-0.475	0.467	-0.339	**0.910**			
	S_2	-0.434	0.694	-0.260	**0.896**			
	S_3	-0.407	0.678	-0.202	**0.885**			
FAIR	S_1	0.314	-0.543	0.321	-0.492	**0.822**		
	S_2	-0.014	-0.213	0.527	-0.275	**0.835**		
	S_3	0.039	-0.208	0.610	-0.198	**0.766**		
PW	S_1	-0.271	0.491	-0.178	0.740	-0.442	**0.845**	
	S_2	-0.384	-0.384	-0.257	0.830	-0.233	**0.875**	
	S_3	-0.384	0.684	-0.223	0.825	-0.229	**0.877**	
TAI	S_1	-0.730	0.197	-0.220	0.377	-0.245	0.190	**0.863**
	S_2	-0.647	0.525	-0.082	0.557	-0.039	0.462	**0.923**
	S_3	-0.599	0.501	-0.104	0.446	0.028	0.389	**0.920**

Notes:
1) The diagonals are the square root of the average variance extracted (AVE) for each factor.
2) ACISP = Affective Commitment to the IS Profession; CFC = Career–Family Conflict; CTRL = Control of Career; EISCE = Exhaustion from IS Career Experience; FAIR = Fairness; PW = Perceived Workload; TAI = Turn-Away Intention
3) Armstrong et al. (2015) study findings = S_1; replication study with Gen Xer sample findings = S_2; replication study with Millennial sample findings = S_3

Our measurement model analyses reveal that construct reliability, convergent validity, and discriminant validity criteria are met. A bootstrapping approach with 500 iterations and 5000 subsamples was applied to assess the significance and relevance of the inter-construct relationships. As all variance inflation factor (VIF) values are below 5 (Hair et al., 2017), and the more stringent 3.3 determined by Kock and Lynn (2012), no critical levels of collinearity are indicated. Next, the structural model is evaluated.

The structural model was evaluated using 1) path coefficients (β), 2) coefficients of determination (R^2), 3) predictive relevance (Q^2), and 4) exogenous construct effect sizes (f^2) as recommended by Ringle et al. (2012) and Hair et al. (2017).

The model evaluation reveals that all paths, except those between the resources and EISCE, are significant. Table 5 summarizes the standardized path coefficients, p-values, and significance indicators for each hypothesized relationship across the studies.

Table 5. Results of Path Analysis

Path		**Regression Weight (Standardized)**			**P-Value**			**Results**		
		S_1	S_2	S_3	S_1	S_2	S_3	S_1	S_2	S_3
H_1	EISCE → TAI (+)	0.005	0.317	0.207	>0.05	0.000	0.003	○	●	●
H_2	EISCE → ACISP (-)	-0.475	-0.434	-0.407	0.001	0.000	0.000	●	●	●

Table 5. Results of Path Analysis

H_3	ACISP → TAI (-)	-0.666	-0.489	-0.489	0.001	0.000	0.000	●	●	●
H_4	EISCE → ACISP → TAI	*See Table 7 for the results of the mediation test.*						●	●	●
H_5	PW → EISCE (+)	0.617	0.620	0.676	0.001	0.000	0.000	●	●	●
H_6	CFC → EISCE (+)	0.076	0.339	0.215	>0.05	0.000	0.000	○	●	●
H_7	FAIR → EISCE (-)	-0.120	-0.026	0.018	0.05	0.438	0.656	●	○	○
H_8	CTRL → EISCE (-)	-0.181	-0.062	-0.028	0.001	0.097	0.463	●	○	○

Notes:
1) Armstrong et al. (2015) study findings = S_1; replication study with Gen Xer sample findings = S_2; replication study with Millennial sample findings = S_3
2) ACISP = Affective Commitment to the IS Profession; CFC = Career–Family Conflict; CTRL = Control of Career; EISCE = Exhaustion from IS Career Experience; FAIR = Fairness; PW = Perceived Workload, TAI = Turn-Away Intention
3) ● = Significant; ○ = Not significant

The R^2 value of TAI reveals that ACISP, EISCE, and NA explain 51.4% and 41.2% of the variance of TAI in the model for Gen Xers and Millennials, respectively. This finding is similar to the 55.5% variance found by Armstrong et al. (2015). Based on Cohen's (1988) classification of effect sizes, the values exceed thresholds for medium (0.30) and large (0.50) effect sizes.

In addition to using R^2 as a criterion of *predictive accuracy*, we examined Stone-Geisser's Q^2 value (Stone, 1974; Geisser, 1974) as a criterion of cross-validated *predictive relevance*. To obtain Q^2, a sample re-use technique known as blindfolding was conducted (Hair et al., 2017). As Wold (1982) recommends an omission distance that is a prime number and Chin (2010) recommends an omission distance between 5 and 10, we specified an omission distance of 7 to run the test. Wold (1982) further suggests that a Q^2 value greater than 0 implies predictive relevance. An evaluation of Q^2 was performed to verify the cross-validated predictive relevance of each endogenous latent variable (Chin, 1998; Geisser, 1974; Stone, 1974). As shown in Table 6, all latent variables exceed this threshold.

Table 6. Coefficients of Determination (R^2) and Predictive Relevance (Q^2) of Latent Variables

	S_1		S_2		S_3	
Latent Variable	R^2	Q^2	R^2	Q^2	R^2	Q^2
ACISP	.225	-	.189	.126	.166	.109
EISCE	.612	-	.773	.608	.705	.545
TAI	.555	-	.514	.409	.412	.339

Notes:
1) Armstrong et al. (2015) study findings = S_1; replication study with Gen Xer sample findings = S_2; replication study with Millennial sample findings = S_3

Armstrong et al. (2015) determined that ACISP is a potential mediator of the relationship between EISCE and TAI. To establish this conclusion, Armstrong et al. (2015) reported a statistically significant Sobel Z-statistics for the indirect effect of EISCE on TAI via ACISP (Sobel, 1982; Helm et al., 2010). Furthermore, it was revealed that the indirect effect is larger than the direct effect. Finally, their analysis revealed that the effect of EISCE on TAI was not significant. We confirm this mediating effect for the samples of Gen Xers and Millennials using the Sobel Z-statistics (see Table 7).

Table 7. Mediation Test of Hypothesis 4 (EISCE → ACISP → TAI)

Study	Mediated Relationship	Sobel Statistic	Sobel Z P-Value

Table 7. Mediation Test of Hypothesis 4 (EISCE → ACISP → TAI)

S_1	EISCE → ACISP → TAI	8.371	< 0.001
S_2		5.596	< 0.001
S_3		5.892	< 0.001

Notes:
1) Armstrong et al. (2015) study findings = S_1; replication study with Gen Xer sample findings = S_2; replication study with Millennial sample findings = S_3
2) ACISP = Affective Commitment to the IS Profession; EISECE = Exhaustion from IS Career Experience; TAI = Turn-Away Intention

We obtained f^2 values by applying Cohen's (1988) pseudo F-test to measure the *effect size* of each exogenous variable on the endogenous variables using SmartPLS. According to Cohen (1988), a value of $f^2 = 0.02$ indicates a small effect, value of $f^2 = 0.15$ indicates a medium effect, and a value of $f^2 = 0.35$ or larger indicates a strong effect. While all exogenous variables contribute to the variance of TAI, it is ACISP that contributes at the highest levels, and an evaluation of the effect size (f^2) revealed that ACISP is the only exogenous variable that has a statistically significant effect size. Furthermore, the direct relationship between EISCE and TAI is far less than when mediated through ACISP. Finally, it is indicated that while Negative Affectivity (the study control variable) has a significant relationship with TAI, its effect size is nonsignificant. See the results of this analysis in Table 8.

Table 8. Evaluation of the Effect Size (f^2) on TAI

Relationship		S_2	S_3
ACISP →	TAI	0.386*	0.334*
EISCE →		0.141	0.050
NA (control) →		0.005	0.008

Notes:
1) Armstrong et al. (2015) findings not reported.
2) Replication study with Gen Xer sample findings = S_2; replication study with Millennial sample findings = S_3
3) ACISP = Affective Commitment to the IS Profession; EISCE = Exhaustion from IS Career Experience; NA = Negative Affectivity; TAI = Turn-Away Intention

As the literature suggests that the Millennials should demonstrate differences when compared to Gen Xers, a permutation test in SmartPLS 3.2.9 was conducted between the two samples. Unlike other forms of multi-group comparisons, such as comparing individual paths using a t-test, the permutation procedure allows for comparisons of the entire model without making assumptions about distribution and requiring equal sample sizes (Crisci & D'Ambra, 2012). Essentially, the permutation procedure determines if there are statistically significant differences between parameter estimates of two pre-defined groups (e.g., Gen Xers and Millennials) (Chin & Dibbern, 2010). When conducting the permutation procedure, we specified the two generational groups, configured the number of permutations to 1000, set the test type to be two-tailed, and set the significance level to be 0.05. As our findings revealed no statistical differences between the two models, we performed independent t-tests to determine if there were significant differences between the sample means for each construct. However, there were only negligible differences. Of interest was whether the Millennials perceived higher levels of exhaustion. The only statistically significant finding was that Gen Xers indicated less TAI, which is understandable as this group would be further along in their careers and would likely be seeking career stability. See the results of this analysis in Table 9.

Table 9. Independent Sample T-Test Results

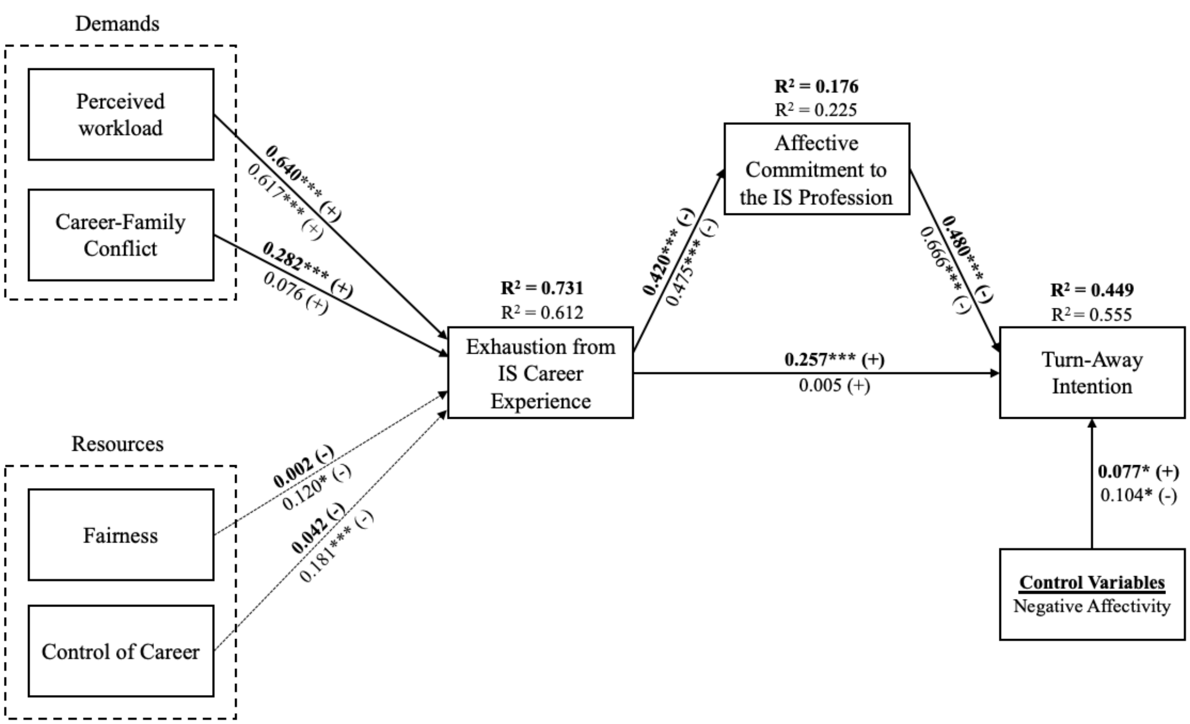
Construct	S_2 (n=252)		S_3 (n=260)		T-Value	Sig.
	Mean	Standard Deviation	Mean	Standard Deviation		

Table 9. Independent Sample T-Test Results

ACISP	4.094	1.546	4.167	1.517	-0.537	n.s.
CFC	4.100	1.641	4.093	1.684	0.040	n.s.
CTRL	5.356	1.183	5.484	1.608	-1.031	n.s.
EISCE	4.322	1.636	4.321	1.704	0.009	n.s.
FAIR	5.475	1.076	5.552	0.965	-0.859	n.s.
PW	4.539	1.545	4.364	1.616	1.254	n.s.
TAI	3.806	1.753	4.208	1.744	-2.602	*
NA	2.834	2.966	1.500	1.532	-0.990	n.s.

Notes:
1) Replication study with Gen Xer sample findings = S_2; replication study with Millennial sample findings = S_3
2) ACISP = Affective Commitment to the IS Profession; EISECE = Exhaustion from IS Career Experience; NA = Negative Affectivity; TAI = Turn-Away Intention; NA = Negative Affectivity (control variable)
3) n.s. = no significance; * p<0.05

As generational differences were not detected, we can examine a combined model. Figure 2 presents the final path model of the combined samples (Gen Xers and Millennials) along with the findings of Armstrong et al. (2015).



Notes:
1) The numbers in the path model represent β; * p < 0.05; ** p < 0.01; *** p < 0.001.
2) Bold text indicates combined replication sample (S_2 and S_3) findings; regular text indicates Armstrong et al. (2015) findings.
3) Bold, solid lines indicate path significance for the combined replication sample (S_2 and S_3) findings; dashed paths are nonsignificant.

Figure 2. Final Combined Model Paths

5 Discussion, Limitations, and Future Research

While our findings largely supported the empirical results of Armstrong et al. (2015), there were notable differences. For instance, although Armstrong et al. (2015) did not find support for H_1 (a positive and significant relationship between EISCE and TAI), we reveal a positive and statistically significant relationship between EISCE and TAI ($\beta = 0.257$, $p < 0.001$). Nevertheless, the magnitude of the direct effect on TAI is negligible ($f^2 = 0.082$). Additionally, Armstrong et al. (2015) suggested that work-demands across the IS career experience would result in EISCE. Contrary to their findings, our results supported the relationship between CFC and EISCE. While different than the original study, this relationship is supported through theory and empirical evidence (Blau, 2007; Lee et al., 2000). Finally, Armstrong et al. (2015) suggested that greater resources would result in reduced EISCE. Specifically, while perceptions of IS career fairness and control of the IS career were shown to influence IS career exhaustion in the original study, the replication did not confirm these results. This inconsistent finding could be attributed to a broader change in the influence of fairness and control of career on EISCE since the original study was conducted. Another explanation is that the significant impact of PW and CFC on EISCE could be rendering FAIR and CTRL nonsignificant. Moreover, differences between the study samples (particularly concerning generational groups and racial diversity) could indicate that the replication study respondents were more desensitized to perceptions of their career resources (e.g., fairness and control of career).

Perhaps, the most surprising finding is that the differences between the models of Gen Xers and Millennials in the IT workforce were not statistically significant. It is possible that workplace programs (e.g., flex-time, training) have created an environment that minimizes perceived differences between generational groups. Similarly, the increasing use of relatively well-established processes and procedures within IS careers may contribute to a normalized and shared understanding of fairness and workload, which would limit the ability to elucidate differences. While burnout has been a topic in the literature regarding the Millennial workforce, we conclude that burnout is not a contextual construct that depends on a unique workforce generation. As generational differences were not indicative of the differences between the two studies, perhaps other factors compelled the changes. One of these factors could simply be the time that has elapsed between the two studies and the effects of societal, economic, and even technological advances. For instance, our data collection occurred during a time of sustained economic growth in the United States. Another possible factor in explaining the conflicting findings may be regional cultural differences. Subjects for the original study were located in the South-Central United States, while samples for this replication included subjects from throughout the United States. However, as this is the first study to examine the effects of generational differences on EISCE, ACISP, and TAI, additional empirical evidence is needed.

This methodological replication makes several important contributions to research and practice. First, researchers benefit from a replication of Armstrong et al. (2015) as their original work involved extending job level constructs to the IS career level. IS research has yet to understand the behavioral aspects of those pursuing IS careers entirely. Furthermore, due to the ongoing lack of workforce resources to meet industry demands, the IS industry must prevent the turn-away of critical human resources. We, therefore, concur with the original recommendations of Armstrong et al. (2015) that an emphasis on communicating realistic IS career expectations should continue to happen, particularly concerning workload and family-career conflicts.

This methodological replication attempted to reproduce the findings of Armstrong et al. (2015) while addressing some limitations of the original study. However, even with a careful methodology, this study introduces several new limitations. First, a large portion of our sample includes IT managers and directors, who may experience different perceptions than more technical staff. Thus, future research could evaluate whether job types influence EISCE, ACISP, or TAI. Second, this study only evaluates perceptions of respondents based on the United States and thus may not be generalizable to other cultural and national contexts. Future research should determine if these relationships are still supported when the hypotheses are tested in the context of IT professionals residing in countries other than the United States.

6 Conclusion

This research sought a methodological replication of the study conducted by Armstrong et al. (2015) that posited and empirically evaluated a research model of EISCE, ACISP, and TAI. We applied the original model but focused on the generational differences. We did not find generational effects on the model between Gen Xers and Millennials. In contrast to the original study, we found empirical support for the relationships between CFC on EISCE and EISCE on TAI. However, we could not replicate the relationship between FAIR and CTRL on EISCE. Our results elucidate the generalizable (e.g., ACISP on TAI) and nongeneralizable (e.g., FAIR on EISCE) relationships developed in the Armstrong et al. (2015) study.

References

Ahuja, M. K., Chudoba, K. M., Kacmar, C. J., McKnight, D. H., & George, J. F. (2007). IT road warriors: Balancing work-family conflict, job autonomy, and work overload to mitigate turnover intentions. *MIS Quarterly*, 31(1), 1-17.

Armstrong, D. J., Brooks, N. G., & Riemenschneider, C. K. (2015). Exhaustion from information system career experience: Implications for turn-away intention. *MIS Quarterly*, 86(3), 499-512.

Bialik, K., & Fry, R. (2019). Millennial life: How young adulthood today compares with prior generations. Pew Research Center.

Blau, G. (2007). Does a corresponding set of variables for explaining voluntary organizational turnover transfer to explaining voluntary occupational turnover? *Journal of Vocational Behavior*, 70(1), 135-148.

Carlson, D., Ferguson, M., Hunter, E., & Whitten, D. (2012). Abusive supervision and work-family conflict: The path through emotional labor and burnout. *The Leadership Quarterly*, 23(5), 849-859.

Chin, W. W. (1998). The partial least squares approach to structural equation modeling. In G. A. Marcoulides (Ed.), *Modern Methods for Business Research* (pp. 295-336). Mahwah, New Jersey: Lawrence Erlbaum Associates

Chin, W. W. (2010). How to write up and report PLS analyses. In E. Esposito Vinzi, W. Chin, J. Henseler, H. Wang (Eds.), *Handbook of Partial Least Squares* (pp. 655-690). Berlin: Springer.

Chin, W. W., & Dibbern, J. (2010). An introduction to a permutation based procedure for multi-group PLS analysis: Results of tests of differences on simulated data and a cross cultural analysis of the sourcing of information system services between Germany and the USA. In E. Esposito Vinzi, W. Chin, J. Henseler, H. Wang (Eds.), *Handbook of Partial Least Squares* (pp. 171-193). Berlin: Springer.

Cohen, J. (1988). *Statistical Power Analysis for the Behavioral Sciences*. Hillsdale, New Jersey: Lawrence Erlbaum Associates.

Creswell, J. W. (2013). *Qualitative Inquiry & Research Design*. Thousand Oaks, California: Sage Publications.

Crisci, A., & D'Ambra, A. (2012). Permutation test for group comparison in PLS path modeling. *Electronic Journal of Applied Statistical Analysis*, 5(3), 339-345.

Cronbach, L. J. (1957). The two disciplines of scientific psychology. *American Psychologist*, 12, 671-684.

Dennis, A. R., & Valacich, J. S. (2014). A replication manifesto. *AIS Transactions on Replication Research*, 1, 1-4.

Ferguson, M., Carlson, D., Hunter, E. M., & Whitten, D. (2012). A two-study examination of work-family conflict, production deviance and gender. *Journal of Vocational Behavior*, 81(2), 245-258.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39-50.

Geisser, S. (1974). A predictive approach to the random effect model. *Biometrika*, 61(1), 101-107.

George, J., & Wallio, S. (2017). Organizational justice and millennial turnover in public accounting. *Employee Relations*, 39(1), 112-126.

Hair Jr, J. F., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2017). *A primer on partial least squares structural equation modeling (PLS-SEM)*. Thousand Oaks, California: Sage Publications.

Helm, S., Eggert, A., & Garnefeld, I. (2010). Modeling the impact of corporate reputation on customer satisfaction and loyalty using partial least squares. In E. Esposito Vinzi, W. Chin, J. Henseler, H. Wang (Eds.), *Handbook of Partial Least Squares* (pp. 515-534). Berlin: Springer.

Jiang, X. R., Du, J. J., & Dong, R. Y. (2017). Coping style, job burnout and mental health of university teachers of the millennial generation. *Eurasia Journal of Mathematics, Science and Technology Education*, 13(7), 3379-3392.

Kim, S. (2012). The impact of human resource management on state government IT employee turnover intentions. *Public Personnel Management*, 41(2), 257-279.

Kock, N., & Lynn, G.S. (2012). Lateral collinearity and misleading results in variance-based SEM: An illustration and recommendations. *Journal of the Association for Information Systems*, 13(7), 546-580.

Korn Ferry (2018). 2030: Labor skills shortage of 4.3 million workers and unrealized output of $449.7 billion. Retrieved November 11, 2019, from https://futureofwork.kornferry.com/sector-perspective/#technology-media-and-telecommunications

Leiter, M. P., & Maslach, C. (2016). Latent burnout profiles: A new approach to understanding the burnout experience. *Burnout Research*, 3(4), 89-100.

Lee, K., Carswell, J. J., & Allen, N.J. (2000). A meta-analytic review of occupational commitment: Relations with person and work-related variables. *Journal of Organizational Behavior*, 9(3), 217-239.

Lee, R. T., & Ashforth, B. E. (1996). A meta-analytic examination of the correlates of the three dimensions of job burnout. *Journal of Applied Psychology*, 81(2), 123-133.

Lu, A. C. C., & Gursoy, D. (2016). Impact of job burnout on satisfaction and turnover intention: Do generational differences matter? *Journal of Hospitality & Tourism Research*, 40(2), 210-235.

Mannheim, K. (1970). The problem of generations. *Psychoanalytic Review*, 57(3), 378-404.

Maslach, C. (1998). A multidimensional theory of burnout. In C. L. Cooper (Ed.), *Theories of Organizational Stress* (pp. 68–85). New York: Oxford University Press.

Maslach, C. & Schaufeli, W. B. (1993). Historical and conceptual development of burnout. In W. B. Schaufeli, C. Maslach & T. Marek (Eds.), *Professional Burnout: Recent Developments in Theory and Research* (pp. 1-16). New York: Taylor & Francis.

Maslach, C., Schaufeli, W. B. & Leiter, M. P. (2001). Job burnout. *Annual Review of Psychology*, 52, 397-422.

Moquin, R., K. Riemenschneider, C., & L. Wakefield, R. (2019). Psychological contract and turnover intention in the information technology profession. *Information Systems Management*, 36(2), 111-125.

Nunnally, J. C., & Bernstein, I. H. (1994), *Psychometric Theory*, *3rd ed*., New York: McGraw-Hill.

Olbrich, S., Frank, U., Gregor, S., Niederman, F., & Rowe, F. (2017). On the merits and limits of replication and negation for IS research. *AIS Transactions on Replication Research*, 3, 1-19.

Petersen, A.H. (2019). How millennials became the burnout generation, *BuzzFeedNews*, Retrieved November 11, 2019, from https://www.buzzfeednews.com/article/annehelenpetersen/millennials-burnout-generation-debt-work

Ringle, C. M., Sarstedt, M., & Straub, D. W. (2012). Editor's comments: A critical look at the use of PLS-SEM in "MIS Quarterly". *MIS Quarterly*, 36(1), iii-xiv.

Ringle, C. M., Wende, S., & Becker, J.-M. (2015). SmartPLS 3. Bönningstedt: SmartPLS. Retrieved from http://www.smartpls.com

Ryder, N. B. (1985). The cohort as a concept in the study of social change. In *Cohort Analysis in Social Research* (pp. 9-44). Berlin: Springer.

Sanghani, R. (2019). How it feels to have 'millennial burnout', *BBC News*, Retrieved November 11, 2019, from https://www.bbc.co.uk/bbcthree/article/c384d54a-0116-437f-83e8-ddbca65b6c06

Schullery, N. M. (2013). Workplace engagement and generational differences in values. *Business Communication Quarterly*, 76(2), 252–265.

Singh, P. (2013). Millennials and the workplace: Challenges for architecting the organizations for tomorrow. *Human Resource Management International Digest*, 21(7).

Smith, N. C. (1970). Replication studies: A neglected aspect of psychological research. *American Psychologist*, 25(10), 970-975.

Stone, M. (1974). Cross-validatory choice and assessment of statistical predictions. *Journal of the Royal Statistical Society*, *Series B*, 36(2), 111-147.

Sobel, M. E. (1982). Asymptotic confidence intervals for indirect effects in structural equation models. *Sociological Methodology*, 13, 290-312.

Wold, H. (1982). Soft modeling: The basic design and some extensions. In K. Jöreskog, S. Wold, H. Wold (Eds.), *Systems under Indirect Observation: Causality, Structure, Prediction*, North Holland: Elsevier Publishing Company.

Worly, B., Verbeck, N., Walker, C., & Clinchot, D. M. (2019). Burnout, perceived stress, and empathic concern: differences in female and male Millennial medical students. *Psychology, Health & Medicine*, 24(4), 429-438.

Wright, T. A., & Cropanzano, R. (1998). Emotional exhaustion as a predictor of job performance and voluntary turnover. *Journal of Applied Psychology*, 83(3), 486.

Yellowbrick (2019). Retrieved November 11, 2019, from https://www.yellowbrickprogram.com/blog/survey-reveals-factors-behind-millennial-burnout

Appendix A: Measurement Scales (Armstrong et al., 2015)

Career Exhaustion (Strongly Disagree to Strongly Agree)

Think about your entire IT career…

I have felt emotionally drained from my work.

I have felt used up at the end of the workday.

I have felt fatigued when getting up in the morning and having to face another day on the job.

I have felt burned out from my work.

Career Fairness (Strongly Disagree to Strongly Agree)

Think about your entire IT career…

My work schedule has been fair.

I think that my level of pay has been fair.

I consider my workload to have been fair.

I feel that my job responsibilities have been fair.

Overall, the rewards I received have been fair.

Career Workload (Strongly Disagree to Strongly Agree)

Think about your entire IT career…

I have felt busy or rushed at work.

I have felt pressured at work.

I have felt that the amount of work I've done has interfered with how well it was done.

I have felt that the number of requests, complaints, or problems I dealt with was more than expected

Career Affective Commitment (Strongly Disagree to Strongly Agree)

I would be happy to spend the rest of my life in this profession.

I enjoy discussion my profession with people outside IT.

I think I could easily become as attached to another profession as I am to this one (*).

I do not feel emotionally attached to this profession (*).

I do not feel a strong sense of belonging to my profession (*).

Career-Family Conflict (Strongly Disagree to Strongly Agree)

The demands of my work interfered with my home and family life.

The amount of time my job took up made it difficult to fulfill family responsibilities.

Things I wanted to do at home did not get done because of the demands my job put on me.

My job produced strain that made it difficult to fulfill family duties.

Career Control - Control (Strongly Disagree to Strongly Agree)

I feel like I am in control of my future in the IT profession.

I feel like I can influence the nature of change in the IT profession (*).

I feel in control of the direction on which my career is headed.

Career Control – Power (Strongly Disagree to Strongly Agree)

I have enough power to control events that might affect my IT career.

In the IT profession, I can prevent negative things from affecting my work situation.

I understand the IT profession well enough to be able to control things that affect me.

Negative Affect (Not at all to Extremely)

Below are a number of words that describe different feelings and emotions. Over the last six months, to what extent have you felt:

Afraid

Distressed

Nervous

Upset

Scared

Irritable

Jittery

Turn-away Intention (Strongly Disagree to Strongly Agree)

I intend to continue working in the IT profession until I retire (*).

I expect to work in a career other than IT sometime in the future.

I frequently think about getting out of the IT profession.

It is likely that I will soon explore career opportunities outside of the IT profession.

(*): Reverse-coded item

About the Authors

Michael A. Erskine received his Ph.D. in Computer Science and Information Systems from the University of Colorado Denver. Prior to joining Middle Tennessee State University as an Assistant Professor, Michael served as the Director of the Educational Technology Center at Metropolitan State University of Denver. His teaching interests include location analytics, web development, and project management. His research interests include educational technology, learner competencies, disaster management, technology governance, and geospatial decision-making. His research has been presented at various international, national, and regional conferences including the International Conference on Information Systems (ICIS), the Americas Conference on Information Systems (AMCIS), and the International Conference on Information Resources Management (ConfIRM). Additionally, his work has been published in *Information Systems Frontiers*, *International Journal of Human-Computer Interaction*, *Computers in Human Behavior*, *Journal of Computer Information Systems*, and *International Journal of Electronic Government Research*. He is a member of the Association for Information Systems, the Project Management Institute, and the Decision Sciences Institute.

Sam Zaza is an Assistant Professor of Information Systems and Analytics in the Jennings A. Jones College of Business at Middle Tennessee State University. Her primary areas of research interest include IT workforce, STEM education, diversity and IT careers, and methodological approaches. Her research has appeared in multiple proceedings including those of the International Conference on Information Systems (ICIS) and the Americas Conference on Information Systems (AMCIS).

Stoney Brooks is an Associate Professor in the Jones College of Business at Middle Tennessee State University. Stoney received his Ph.D. in Management Information Systems from Washington State University. Stoney's research is published in numerous journals, including: *Communications of the Association for Information Systems*, *Journal of Computer Information Systems*, *Computers in Human Behavior*, *Journal of Small Business Management*, *Computer Networks*, *Internet Research*, at the Americas Conference on Information Systems (AMCIS), and in *Green Business Process Management: Towards the Sustainable Enterprise* from Springer. Stoney is actively researching negative effects of technology usage, social media addiction, and adoption of autonomous vehicles. He is a member of the Association for Information Systems and the Executive Treasurer for the Society to Advance Information Systems in MBAA International.

Scott J. Seipel is an Associate Professor of Information Systems and Analytics at Middle Tennessee State University's Jones College of Business. He received his Ph.D. in statistics/operations research from the University of Texas at Arlington. As a statistician and a data scientist, his research interests follow the data no matter the size.