

LEARNER AUTONOMY PROFILE: AN ESTIMATION OF NORMATIVE STATISTICS FOR NONTRADITIONAL ADULTS IN THE UNITED STATES

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ABSTRACT

The Learner Autonomy Profile (LAP) is a battery of five instruments: the Inventory of Learner Desire (ILD), the Inventory of Learner Resourcefulness (ILR), the Inventory of Learner Initiative (ILI), the Inventory of Learner Persistence (ILP), and the Appraisal of Learner Autonomy (ALA). For over 15 years, the LAP (licensed to Human Resource Development Enterprises; HRDE) has been used in research on learner autonomy as well as the efforts of HRDE-certified coaches to facilitate the strengthening of learner autonomy in clients. To date, over 2,000 individuals have taken this battery around the world thereby producing multiple nonprobability samples. In 2017, Ponton presented normative descriptive statistics of mean and standard deviation for the ALA using a previously unpublished estimation technique on a nonprobability sample ($N = 817$) arguably representing nontraditional adults (aged 25-64) in the United States with at least a high school education. The purpose of this article is to extend this previous analysis and provide estimates for the normative descriptive statistics associated with the ILD, ILR, ILI, and ILP thereby completing the LAP battery.

KEYWORDS: Learner Autonomy Profile, learner autonomy, normative statistics, descriptive statistics, estimation technique.

1. INTRODUCTION

In 1992, Confessore theorized four conative factors—desire, resourcefulness, initiative, and persistence—as representing the defining characteristics of an autonomous learner who exhibits personal agency in learning. “Conative” is used in conjunction with autonomous learning because “conation refers to his [sic, i.e., the agent’s] behavioral intentions” (Fishbein & Ajzen, 1975, p. 12) that leads to intentional learning. As associated instruments were needed for research, Meyer (2001), Carr (1999), Ponton (1999), and Derrick (2001) developed the Inventory of Learner Desire (ILD), the Inventory of Learner Resourcefulness (ILR), the Inventory of Learner Initiative (ILI), and the Inventory of Learner Persistence (ILP), respectively. After further refinement (Park & Confessore, 2002), these four instruments were conglomerated as the Learner Autonomy Profile (LAP), which is licensed to Human Resource Development Enterprises (HRDE) in its efforts to both study (e.g., Ponton, Carr, & Derrick, 2004; Ponton, Derrick, & Carr, 2005; Ng & Confessore, 2010) as well as develop (via HRDE-certified coaches) learner autonomy among adult learners.

The ILD (originally titled the Inventory of Intentional Behavior; Meyer, 2001) measures the presence of three constructs: basic freedoms, managing power, and acquired skills. Not contextualized to learning, the ILD measures salient constructs related to an adult's ability to act agentically. The ILR (Carr, 1999) measures the degree to which an adult (a) anticipates the future benefits of learning, (b) prioritizes learning over nonlearning activities, (c) chooses to participate in learning versus nonlearning activities, and (d) solves problems that interfere with desired learning activities. The ILI (Ponton, 1999) assesses the presence of the following intentions as manifest by an adult learner: goal-directedness, action-orientation, persistence in overcoming obstacles, active-approach to problem solving, and self-startedness. The ILP (Derrick, 2001) measures construct that support perseverance in adult learning: volition, self-regulation, and goal-directedness. Bandura (1986, 1997) developed a social cognitive theory that incorporates self-efficacy—a self-perception of the ability to act successfully—as an important factor in motivating action and, thus, personal agency. Because of this, Ponton, Derrick, Hall, Rhea, and Carr (2005; [republished] 2016) developed the Appraisal of Learning Autonomy (ALA) as a measure of self-efficacy in autonomous learning, which was added to the LAP by HRDE.

The LAP (ILD, ILR, ILI, ILP, and ALA) has been administered to well over 2,000 participants in research studies and HRDE coaching activities around the world but primarily in the United States (U.S.) and Southeast Asia. Ponton, Carr, Schuette, and Confessore (2010, [republished] 2016) presented intercorrelations between all five scales where all correlations were significant at the .01 level and ranged from .391 to .893 ($N = 2,074$). Due to the varied uses, the LAP database of participants is not a probability sample of any particular population.

In 2017, Ponton used a then unpublished estimation technique (subsequently published in Ponton & Rovai, 2018) to develop normative statistics—mean and standard deviation—for the ALA for U.S. nontraditional adults (age range 25 to 64) with minimally a high school education. Normative descriptive statistics are often needed as comparative values, and Ponton (2018) used these estimated ALA statistics in showing the extent to which professors exceed the population in self-efficacy in autonomous learning. The purpose of this article is to replicate the analysis performed by Ponton (2017) and develop normative statistics for the ILD, ILR, ILI, and ILP with respect to the same defined population of (minimally) high school educated, nontraditional U.S. adults.

2. METHOD

2.1 Estimation technique

Ponton and Rovai (2018) presented a method to calculate the exact pooled mean and standard deviation for two or more groups if given the sample size, mean, and standard deviation for each group. Ponton and Rovai discussed a modification to this exact solution in order to provide estimation for normative statistics of a population defined by known proportions of salient population characteristics when given a nonprobability sample. As presented in Ponton (2017), the technique is as follows:

Let:

k = number of groups

n_i = sample size of i^{th} group

w_i = weighting of i^{th} group

M_i = mean of i^{th} group

$N = \sum_{i=1}^k n_i$ = pooled sample size.

The mean square statistic is given by

$$MS = \frac{n-1}{n} s^2. \quad (1)$$

For the pooled sample, the pooled mean is the weighted mean given by

$$M_p = \sum_{i=1}^k w_i M_i. \quad (2)$$

The weighted solution for the pooled mean square is then given by

$$MS_p = \sum_{i=1}^k w_i [MS_i + (M_i - M_p)^2] \quad (3)$$

where the pooled variance and standard deviation, respectively, are given by

$$s_p^2 = \frac{N}{N-1} MS_p \quad (4)$$

$$s_p = \sqrt{s_p^2} . \quad (5)$$

Using data presented by Ryan and Bauman (2016) on the U.S. adult population, Ponton (2017) developed the weighting factor (w ; see eq. 2) presented in Table 1 that corresponds to the demographic variables captured by the LAP regarding age, education, and gender.

Table 1. Weighting Factors for U.S. Adults Aged 25 to 64

Age	Education (Max)	Gender	w
25-34	HS	Male	.078
		Female	.078
	Bachelor	Male	0.36
		Female	0.36
	Graduate	Male	0.16
		Female	0.16
35-44	HS	Male	0.71
		Female	0.71
	Bachelor	Male	0.31
		Female	0.31
	Graduate	Male	0.19
		Female	0.19
45-64	HS	Male	0.161
		Female	0.161
	Bachelor	Male	0.56
		Female	0.56
	Graduate	Male	0.34
		Female	0.34

Note. 50-50 weighting by gender used.

For the present study, the goal was to calculate M_p and s_p (i.e., the normative mean and standard deviation, respectively) for the ILD, ILR, ILI, and ILP.

2.2 DATA

Beginning with a database that exceeded 2,000 participants, all cases corresponding with a study name (included in the database) that suggested a non-U.S. study were deleted. For the targeted

population of interest—U.S. nontraditional adults (age range 25 to 64) with minimally a high school education—a nonprobability sample of size 817 was generated.

3. FINDINGS

Descriptive statistics for the raw data are presented in Tables 2 through 5 for the ILD (possible range 0-330), ILR (possible range 0-530), ILI (possible range 0-440), and ILP (possible range 0-340), respectively. Table 6 presents the descriptive statistics (i.e., mean and standard deviation) for the raw data and the estimated normative statistics using equations 1-5. Note that as more data are acquired, further refinements to these estimates can be made using the method presented.

Table 2. Inventory of Learner Desire: Descriptive Statistics

Age	Education (Max)	Gender	<i>M</i>	<i>s</i>	<i>n</i>
25-34	HS	Male	241.1	37.6	6
		Female	255.6	30.2	35
	Bachelor	Male	248.0	30.0	12
		Female	255.0	29.4	51
	Graduate	Male	254.1	30.0	30
		Female	260.3	35.2	96
35-44	HS	Male	231.1	96.0	2
		Female	246.8	45.8	40
	Bachelor	Male	267.4	25.1	10
		Female	260.6	29.7	44
	Graduate	Male	256.1	28.2	66
		Female	259.7	31.7	110
45-64	HS	Male	237.2	38.0	9
		Female	244.4	37.3	29
	Bachelor	Male	258.0	31.7	6
		Female	258.2	36.0	54
	Graduate	Male	258.1	29.0	63
		Female	266.9	31.5	154

Note. *M* = 258.3 and *s* = 33.1 for the raw data (*N* = 817).

Table 3. Inventory of Learner Resourcefulness: Descriptive Statistics

Age	Education (Max)	Gender	<u>M</u>	<u>s</u>	n
25-34	HS	Male	415.0	63.4	6
		Female	418.2	54.2	35
	Bachelor	Male	322.6	68.6	12
		Female	405.2	49.4	51
	Graduate	Male	382.8	51.3	30
		Female	394.7	53.4	96
35-44	HS	Male	404.9	80.8	2
		Female	411.0	69.0	40
	Bachelor	Male	432.1	43.4	10
		Female	408.1	56.1	44
	Graduate	Male	404.8	54.1	66
		Female	414.2	59.8	110
45-64	HS	Male	407.6	52.5	9
		Female	413.0	49.2	29
	Bachelor	Male	412.8	38.4	6
		Female	387.3	59.7	54
	Graduate	Male	410.2	50.3	63
		Female	424.6	55.1	154

Note. M = 407.7 and s = 57.3 for the raw data (N = 817).

Table 4. Inventory of Learner Initiative: Descriptive Statistics

Age	Education (Max)	Gender	<i>M</i>	<i>s</i>	n
25-34	HS	Male	354.0	48.8	6
		Female	343.4	55.7	35
	Bachelor	Male	268.3	52.7	12
		Female	320.7	49.8	51
	Graduate	Male	319.0	40.4	30
		Female	322.9	57.1	96
35-44	HS	Male	318.8	61.2	2
		Female	335.9	72.7	40
	Bachelor	Male	348.9	49.8	10
		Female	328.4	62.1	44
	Graduate	Male	333.0	49.9	66

		Female	348.4	55.8	110
45-64	HS	Male	343.6	39.2	9
		Female	346.5	50.5	29
	Bachelor	Male	361.1	33.1	6
		Female	308.4	61.9	54
	Graduate	Male	340.8	45.1	63
		Female	352.5	48.9	154

Note. $M = 335.8$ and $s = 55.6$ for the raw data ($N = 817$).

Table 5. Inventory of Learner Persistence: Descriptive Statistics

Age	Education (Max)	Gender	M	s	n
25-34	HS	Male	289.4	41.8	6
		Female	278.5	36.5	35
	Bachelor	Male	218.6	50.4	12
		Female	264.4	34.3	51
	Graduate	Male	259.6	32.6	30
		Female	266.9	42.0	96
35-44	HS	Male	249.8	65.4	2
		Female	270.9	53.7	40
	Bachelor	Male	279.7	33.6	10
		Female	266.9	44.8	44
	Graduate	Male	268.0	40.9	66
		Female	278.6	42.7	110
45-64	HS	Male	271.7	25.6	9
		Female	281.4	38.2	29
	Bachelor	Male	288.2	23.9	6
		Female	254.9	41.5	54
	Graduate	Male	275.2	35.8	63
		Female	282.9	37.1	154

Note. $M = 272.0$ and $s = 41.2$ for the raw data ($N = 817$).

Table 6. Raw Data and Pooled Estimates: Mean and Standard Deviation

Instrument	<i>M</i>	<i>s</i>	<i>MS_p</i> (eq. 2)	(eq. 5)
ILD	258.3	33.1	249.5	38.9
ILR	407.7	57.3	408.5	56.7
ILI	335.8	55.6	338.5	53.1
ILP	272.0	41.2	272.8	<u>40.6</u>

Note. N= 817.

4. DISCUSSION

Other than the ILD, the difference between the raw data and pooled estimate for the mean is less than 1%; for the ILD, the difference is 3.5% (see Table 7). The larger differences are with respect to the standard deviation with again the largest difference found with the ILD (14.9%) followed by the ILI (4.7%), ILP (1.5%), and ILR (1.1%) as per Table 7.

Table 7. Percent Difference Between Raw Statistics and Pooled Estimates

Instrument	<u>Difference in Mean (%)</u>	<u>Difference in Standard Deviation (%)</u>
ILD	3.5	14.9
ILR	-0.2	1.1
ILI	-0.8	4.7
ILP	-0.3	<u>1.5</u>

Note. Pooled estimates used as the reference (N = 817).

The present findings suggest that there can be a large difference (particularly with respect to the ILD) in interpretive meanings attributed to the LAP findings of studies designed to assess differences between targeted groups and the population of U.S. nontraditional adults (age range 25 to 64) with minimally a high school education. As such, it is highly recommended to use the pooled estimates presented. The estimation technique outlined (Ponton, 2017)—derived from an exact mathematical solution (Ponton & Rovai, 2018)—offers a direct method of estimation that should be considered for other instruments in developing similarly important normative descriptive statistics that can be used in comparative studies.

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