Segment Data Decision-Usefulness Model: An Exploration

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What are the attributes of decision-useful data? Answering that question with a workable model could facilitate developing more decision-useful accounting standards, disclosing more decision-useful data, and verifying the data's decision-usefulness. Relative to segment data, this two-phased mixed methods study explores such a model. Phase one is qualitative; construct measures and a questionnaire were developed. Phase two is quantitative; 1,600 investors were surveyed and the measures assayed. Fifty-five (3.4%) usable responses were obtained and analyzed using partial least squares. Our measures, are reliable and display convergent and discriminant validities. Moreover, our model has predictive ability and thus utility.

INTRODUCTION

What are the attributes of decision-useful data? That question is fundamental for the Financial Accounting Foundation (FAF) trustees and its Post-Implementation Review (PIR) teams[1]. To put it another way, how should one objectively test the decision usefulness of accounting disclosures? Answering this question with a workable model would facilitate the development of more decision-useful accounting standards, disclosure of more decision-useful data, and verification of the data's perceived decision-usefulness.

Firms' issuance of more decision-useful disclosures would prevent or mitigate the persistent discontent of professional investors with U.S. firms' segment data disclosures (FAF, 2012; Fleishman-Hillard Research, 2000; Knutson, 1993). Investor discontent led the FASB to issue Statement of Financial

Accounting Standards Number 131 (SFAS No. 131), "Disclosures about Segments of an Enterprise and Related Information" (FASB 1997), to replace its predecessor, SFAS No. 14, "Financial Reporting for Segments of a Business Enterprise" (FASB 1976).

Information released under the current standard has attracted the attention of academic researchers and a PIR team. Academic researchers reported firms are disclosing different segment profit measures (Street, Nichols, & Gray, 2000). These researchers also reported post-SFAS No. 131 segment disclosures, compared to pre-SFAS No. 131 disclosures, reveal more segments and more data about each segment (Herrmann & Thomas, 2000; Street et al., 2000). Additionally, they reported that only certain firm types are revealing more segments (Berger & Hann, 2007), and that firms which heavily rely on external funding reveal greater differences in segment profitability (Ettredge, Kwon, Smith, & Stone, 2006). However, another researcher reported that segment data releases of 200 *Fortune 500* companies from 2004 thru 2013 reveal no improvement in the number of segments disclosed or number and types of line items disclosed per segment (Bell, 2015).

The PIR team reported findings similar to those of academic researchers. However, it uniquely reported that investors perceive SFAS No. 131 disclosures to be more relevant and reliable than SFAS No. 14's. Nevertheless, it also reported that investors find these disclosures are sometimes insufficient for making decisions. Moreover, they would prefer more consistency in the line items reported by firms with similar business activities, and in the development of those items. Further, they would like segment cash flow, gross margin and working capital information. Notably, the team acknowledged that its procedures did not permit drawing statistically valid inferences, and that its conclusions are subjective (FAF, 2012, p. 4).

Despite the FASB's motive for issuing SFAS No. 131, prior researchers' mixed findings, and the PIR team's endeavor, no method for drawing statistically valid inferences about investors' segment data decision-usefulness perceptions has been offered. Hence, investors' perceptions have not been examined objectively.

We demonstrate just such a method for objectively assessing investors' segment data decision-usefulness perceptions. To do so, we employ the Segment Data Decision-Usefulness Prediction model (SDDPM)[2 3]. Its variables (data qualities) predict (Shmueli, 2010) Decision Usefulness and thereby facilitate the objective assessment of whether or not segment data are decision-useful.

To achieve our aim, we survey investors to measure their perceptions of the decision-usefulness of U.S. domiciled firms' reported products and services segment disclosures. We use partial least squares (PLS) to explore the SDDPM objectively. These are our research questions:

1) What are the attributes of the indicators used to measure the SDDPM's data qualities?

2) What are the attributes of the data qualities that compose the SDDPM?

3) Which SDDPM data qualities most influence investors' decision-usefulness perceptions?

Our study is significant for two reasons. First, segment data are "vital, essential, fundamental, indispensable, and integral to the investment process" (Knutson, 1993). Hence, segment data decision usefulness persistently interests investors. This is a strong argument for exploring a method for objectively assessing segment data decision usefulness.

Second, our study could be useful to the FASB and the FAF. That is, standard-setters want to understand better the qualities that compose decision usefulness and the relations among them (FASB, 2010; Barth, 2006). Our study employs the SDDPM's qualities rather than the FASB's [4]. Nevertheless, in the context of segment data, we shed light on how to assess decision usefulness. Our procedures may benefit PIR teams, as the employment of similar procedures would enhance their reviews' robustness and objectivity.

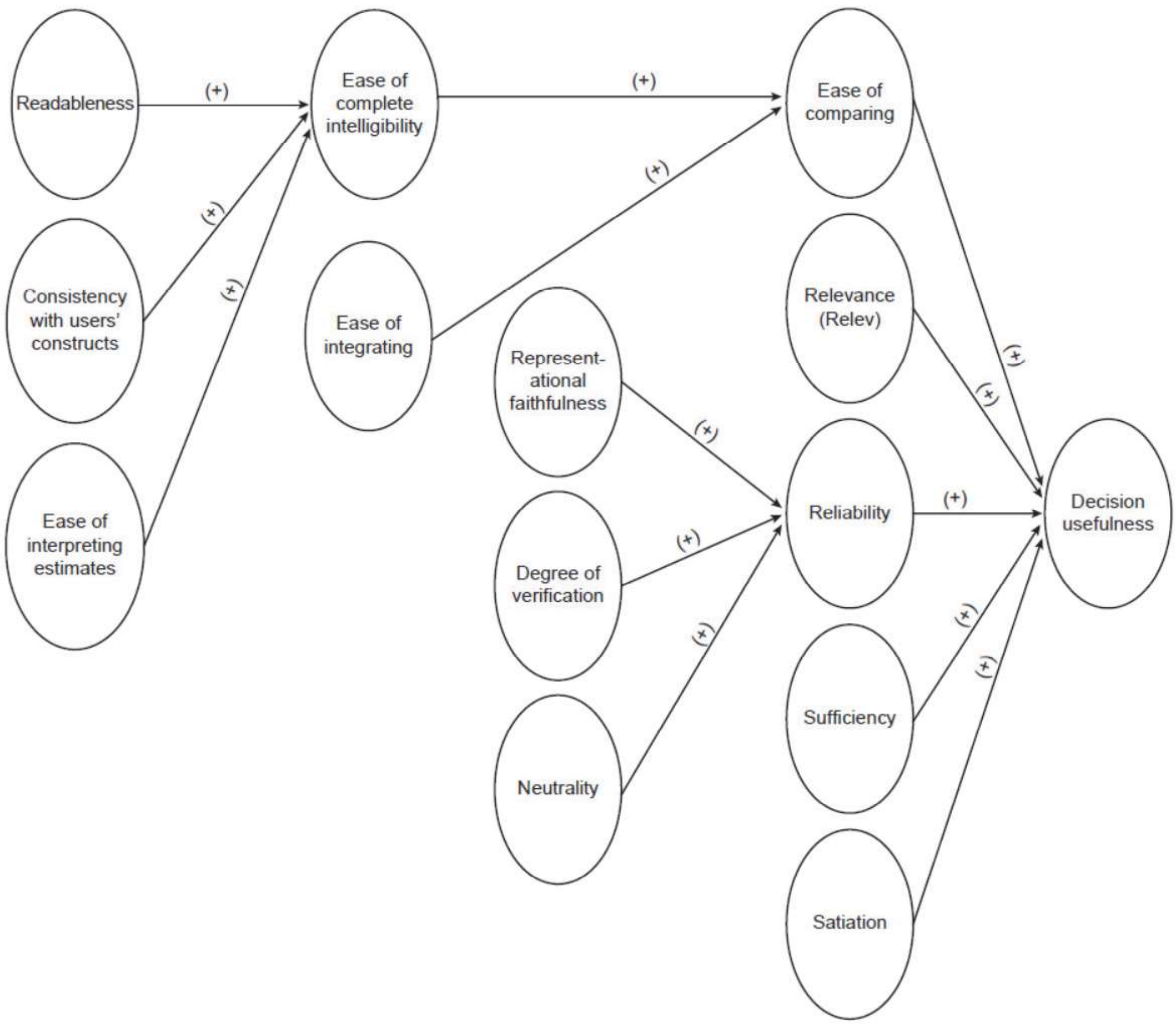
Our paper is organized as follows. Respectively, we describe the SDDPM, our target population, research design, and study phases one and two. Lastly, we summarize and conclude.

SDDPM AND OUR TARGET POPULATION

Fourteen data qualities compose the SDDPM, depicted in Figure 1. Decision Usefulness is the primary dependent latent variable (LV). Ease of Comparing, Relevance, Reliability, Sufficiency, and Satiation predict Decision Usefulness. Ease of Complete Intelligibility and Ease of Integrating predict Ease of Comparing. Readableness, Consistency with Users' Accounting Constructs, and Ease of Interpreting Accounting Estimates predict Ease of Complete Intelligibility. Lastly, Representational Faithfulness, Degree of Verification, and Neutrality predict Reliability. Each predicted data quality has a direct positive association with its antecedents. Tollerson et al. (2015) did not address the relative theoretical importance of the antecedents, nor do we. Appendix A Tables A.1-A4 present the SDDPM's LV definitions.

Professional investors most interested in segment data employ the fundamental analysis[5] investment decision-making approach. These investors have a keen interest in products and services segment data and primarily employ it "to better understand firms." They make one of three decision types: buy-side, sell-side, or adviser-side. Those making buy-side equity decisions represent the interests of banks, foundations or endowments, government or regulatory agencies, insurance companies, investment companies, mutual funds, corporate plan sponsors, public plan sponsors, or unions. Those making sell-side equity decisions represent the interests of brokers, dealers, or investment banks. Those making investment adviser-side equity decisions represent the interests of investment management counseling firms, investment consulting firms, or financial publishers. The investors just described are fundamental-equity investors (Tollerson et al., 2015); these compose our target population. Next we describe our research design.

FIGURE 1
THEORETICAL SEGMENT DATA DECISION-USEFULNESS PREDICTION MODEL
Source: Tollerson, Chin, And Gamble (2015). Reproduced with permission.



RESEARCH DESIGN

To answer our research questions, we employed a two-phased sequential exploratory mixed methods research design (Creswell & Clark, 2011). The first was qualitative; we developed construct measures for SDDPM LVs and devised a mail questionnaire. The second was quantitative; we executed our survey and employed the PLS (Chin, 1998, 2010; Chin & Newsted, 1999) structural equation modeling (SEM) approach to examine the SDDPM.

PHASE ONE: CONSTRUCT MEASURES AND QUESTIONNAIRE DEVELOPMENT

Our questionnaire is the mechanism whereby we mixed our qualitative (phase one) construct measures with our quantitative (phase two) work (Creswell & Clark, 2011). To create the construct measures we employed the SDDPM LV definitions, and composed 41 questions. Questionnaire development followed Dillman (2000).

Our initial questionnaire development task was to list the questions sequentially. A professional investor who employs the fundamental analysis investment decision-making approach reviewed these questions. The review's (pretest's) purpose was to increase the odds that respondents would react positively to our questions and interpret each as intended. Applying feedback from the professional investor, we amended the questions and their sequence. Next, we created the first questionnaire draft, which was pretested by two accounting professors who were otherwise not involved in our study. Each is knowledgeable about accounting qualities, segment reporting and surveys. They examined the instructions, questions and navigational aids for errors and omissions. Applying their feedback, we amended the draft. A graphic artist created a booklet questionnaire. Our investor and the University of Houston Cougar Fund MBA and MS students answered (pretested) it. We choose these students because they manage a multi-million dollar fund and employ the fundamental analysis decision-making approach. Within 15 minutes, most pretesters answered the questionnaire; applying their feedback, we again amended it.

Our questionnaire instructions ask potential respondents to answer just the demographic questions if they do not employ the annual report, 10-K, or 10-Q disclosures of U.S. domiciled firms that disclose products and services segments. The first questionnaire section includes a question that measured whether respondents used these disclosures "*to better understand firms*", which is investors' primary reason for using segment data (Tollerson et al., 2015). The last questionnaire section includes demographic questions designed to assess whether respondents employ the fundamental approach to decision-making. Thus, we used instructions and questions to increase the odds that our SDDPM analyses only include responses from our target population.

Questionnaire sections two through four pertain to SDDPM LVs. All, except one, were measured using a seven-point Likert scale (-3 to +3) measuring from strongly disagree to strongly agree. We employed a semantic differential scale to measure Satiation. We worded all Likert scale questions, except one, either neutrally or positively. Most LVs had at least three questions. See Appendix B for the operationalized SDDPM LVs definitions and corresponding questionnaire questions, indicators, and scale descriptions.

PHASE TWO: SURVEY ADMINISTRATION AND PLS ANALYSES

Phase two comprised two periods. In the first, we administered and assessed our survey following Dillman (2000). In the second, we explored the SDDPM using PLS.

Survey Administration and Assessment

Survey administration procedures included selecting and contacting our sample population, and determining and analyzing our usable response rate. Fundamental-equity investors are our study's target population. We selected potential participants using a non-public database. Our sample frame included: 1) investors with attributes indicating they use the fundamental analysis investment approach in making U.S. equity investment decisions; 2) those with attributes indicating they use reported products and services segment disclosures; and 3) those for whom we had usable valid addresses. We employed random sampling procedures to select a sample of 1,600 investors. Potential participants were offered confidentiality.

Survey administration began February 16, 2009 and ended May 4, 2009. Potential participants received up to five contacts: an announcement letter, the questionnaire, a thank-you postcard, a replacement questionnaire and a telephone call. Correspondence was personalized, stamped and sent via first class mail. The announcement and questionnaire cover letters asked those who chose not to participate to just mail back their questionnaire.

We received responses from 163 (10.2%) investors. Sixty-six (4.1%) answered questions concerning SDDPM LVs. Responses usable for PLS analysis were obtained from 55 (3.4%). Of the usable responses, 24 (44%) were received from investment advisers, 18 (33%) from sell-siders, 10 (18%) from buy-siders, and 3 (5%) from unemployed or retired individuals. We examined early and late responders' demographic differences. (The former mailed their questionnaires before we started our telephone calls.) Early and late responders are demographically similar.

From April 23, 2009 through May 4, 2009, we called a random sample of 333 non-responders and confirmed 198 (59.5%) addresses. We assert that our address-validating tactics reduced the odds that non-response is due to invalid addresses. Our telephone contacts said that due to the 2008 financial crisis, professional investors were counseled not to voice opinions to industry outsiders. Accordingly, it is likely that the crisis negatively impacted our response rate.

To assess our usable response rate, we examined the CFA Institute's rates for its e-mail survey[6] studies of U.S. investment professionals. From March 2008 to July 2009 (before and just after the crisis), six studies were conducted; usable rates ranged from 4.5% - 7% (CFA Institute, 2009). Our rate, of 3.4%, is just below their lowest. Accordingly, ours is acceptable.

SDDPM PLS Analyses

Increasingly, accounting researchers are using PLS to explain complex LVs (Dowling, 2009; Nitzl, 2016; Young, 2013). We assessed the SDDPM using PLS (Chin, 1998), a causal modeling SEM approach. We chose a causal modeling rather than a traditional analysis technique (e.g. multidimensional scaling and factor analysis) because the former are superior. They permit the explicit inclusion of measurement error and the conceptualization of LVs as abstract unobservable constructs (Fornell & Bookstein, 1982).

PLS, a variance component-based SEM approach, is an alternative to covariance-based forms of SEM (CBSEM), of which LISREL is the best known (Chin & Newsted, 1999). We chose PLS for a philosophical reason. Our aims are model exploration, prediction, and application. For these aims, PLS is apt. If a model existed, and if our aims had been further testing and development, then a CBSEM approach might have been warranted (Chin, 1998). PLS imposes minimal demands on measurement scales, error distributions, and sample size (Wold, 1985). These demands also motivated our use of it, as we developed and used new measures, and as our attained sample size is not ideal.

Evaluation of Theoretical Model

PLS estimates two models coincidently: the measurement and structural. Hence, the theoretical model is usually evaluated in two steps: first the measurement model reliability and validity, and second, that of the structural model. These steps foster the use of only reliable and valid measures to draw conclusions about LV relations (Chin, 1998). We estimated the models using PLS-Graph (3.10) (Chin, 2001).

Measurement model

A LV is measured using reflective or formative indicators, or both. Reflective indicators are LV effects; these indicators are assumed to correlate with each other and with the LV. Formative indicators create or cause LV change (Fornell & Bookstein, 1982). These need not correlate with each other or have high internal consistency (Chin, 1998). Our measurement model comprises only reflective indicators. We evaluated these at the indicator and LV levels. Figure 2 depicts our measurement model.

For measurement models with only reflective indicators, the PLS sample size data requirement is ten times the largest of these: (1) the number of indicators of the LV with the greatest number of indicators (indicator level), or (2) the number of antecedents of the LV with the greatest number of antecedent LVs (LV level). That largest value is the size of the largest regression performed during the PLS process

(Chin, 2010). Herein, the largest regression performed uses five predictors. Thus, our sample size of 55 is reasonable, though a larger one would have better detected small effect sizes.

Table 1 provides indicator descriptive statistics and shows our measurement model has 41 indicators. As previously stated, we used a semantic differential scale to measure the Satiation LV's indicators (Q29, Q32a and Q32b). These have negative means, suggesting investors desire more segment data. A Likert scale was used to measure the other indicators. Except for one, Biased (Q17a; Neu1), the questions were neutrally or positively worded. Table 1 shows positive means for the 38 indicators. The Biased mean is positive because we reverse coded it; this positive mean suggests segment data are not biased.

Indicator Level Analyses. At the indicator level, we evaluated our measurement model by examining each indicators' reliability and its convergent and discriminant validities. One assesses indicator-level reliability by examining the loadings (simple correlations) of the indicators with their corresponding LVs. An indicator to LV loading is a correlation. Therefore, the square of the loading is a variance (Chin, 2010).

Loadings should be 0.70 or higher, implying 50 percent (0.70^2) or more of the variance is due to the LV. This suggests the indicator shares more variance with its LV than with measurement error (Chin, 2010). For exploratory models lower threshold values are advocated: 0.50 (Straub, 1989), 0.45 (Lewis, Snyder, & Rainer, 1995), or 0.30 (Lederer & Sethi, 1992).

Table 2 shows all loadings, except one, are above the 0.70 threshold. Most are above 0.80. Relev1's loading (0.60) is below 0.70, but above the highest exploratory model threshold. Our loadings show individual indicators share more variance with the intended LV than with measurement error. Thus our indicators are individually reliable.

Chin (2010) observes indicators should exhibit convergent and discriminant validity. Indicator-level convergent validity is the extent to which an indicator block strongly expresses its LV. High convergent validity is expressed by high and similar magnitude loadings. Wide block ranges (e.g. 0.50 to 0.90) may not represent the same LV; narrow block ranges (e.g. 0.70 to 0.90) increase confidence that all indicators converge (i.e. estimate the same LV).

Convergent validity is assessed by scanning down a column of an indicator to LV loadings and cross loadings table (Chin, 2010). Table 2 shows high loadings and a narrow range for each indicator block; our indicators converge.

Chin (2010) observes that indicator-level discriminant validity is defined as the extent to which an indicator is more strongly correlated with its intended LV than with others. Discriminant validity is assessed by scanning across a row of an indicator to LV loadings and cross loadings table. Table 2 shows low cross loadings for indicators that are not intended to measure a LV; our indicators display discriminant validity.

Table 2 displays high indicator reliability and convergent and discriminant validities.

FIGURE 2
MEASUREMENT MODEL

See Appendix A Tables A1-A4 for latent variable definitions. The Q's identify questionnaire question numbers. See Appendix B for corresponding questions. Letters in parentheses are latent variable indicator name pre-fixes. Oval shapes are latent variables; rectangles are indicators.

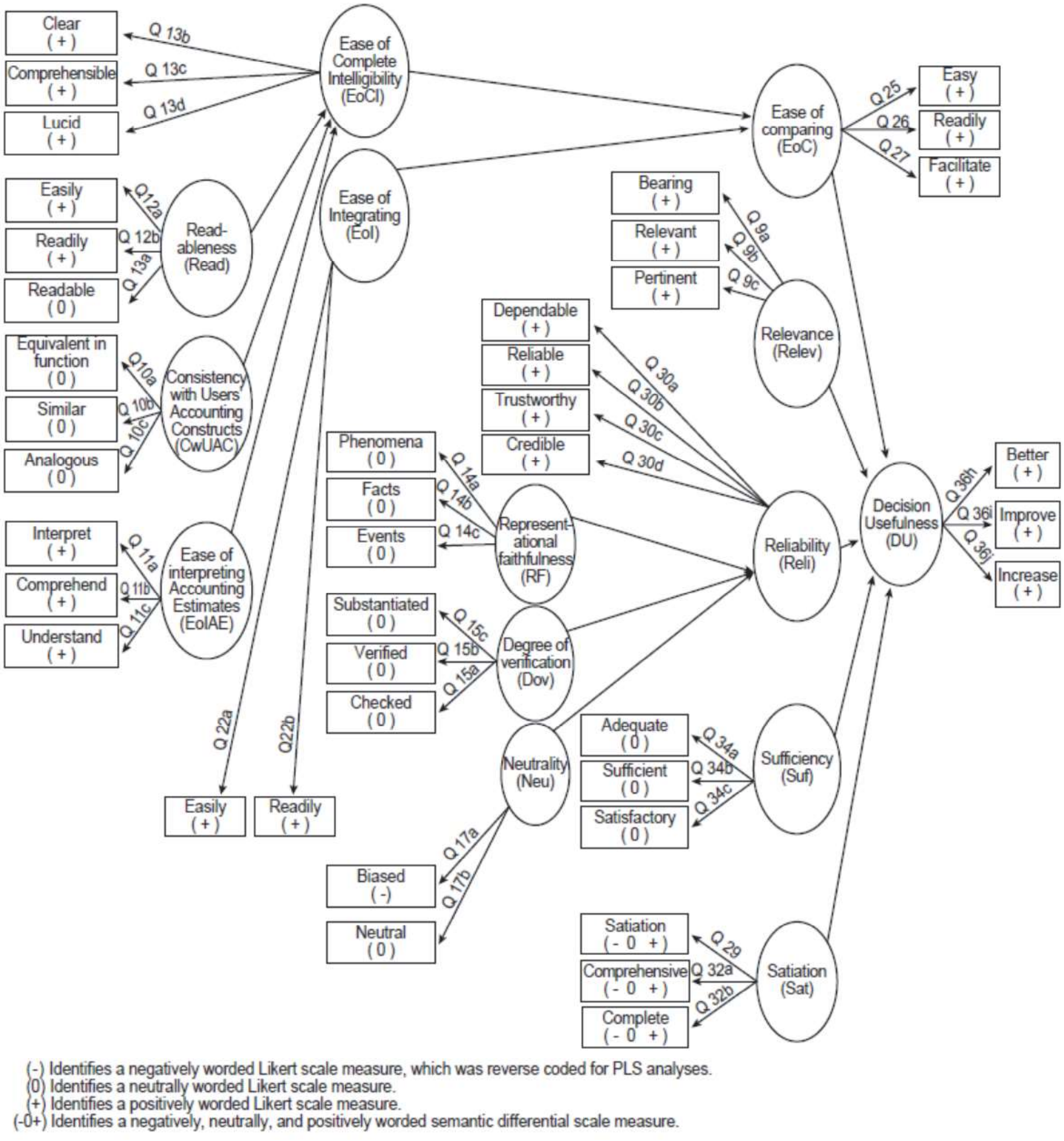


TABLE 1
DESCRIPTIVE STATISTICS

Latent Variable Names	Questionnaire Question #'s & Key Word(s)		Indicator Names	Mean	Variance	Std. Dev.	Skewness	Kurtosis
Readableness	**Q**12a	Easily	Read1	1.500	1.020	1.010	-0.5193	3.0915
	Q12b	Readily	Read2	1.400	1.207	1.099	-0.7787	3.7442
	Q13a	Readable	Read3	1.5904	0.6907	0.8311	-1.0200	4.5197
Consistency with Users' Accounting Constructs	**Q**10a	Equivalent in Function	CwUAC1	0.721	1.322	1.150	-0.1828	2.6009
	Q10b	Similar	CwUAC2	1.1220	0.9658	0.9828	-0.1126	2.3244
	Q10c	Analogous	CwUAC3	0.782	1.347	1.161	-0.5118	3.8415
Ease of Interpreting Accounting Estimates	**Q**11a	Interpret	EoIAE1	1.185	1.040	1.020	-0.4976	2.7110
	Q11b	Comprehend	EoIAE2	1.2908	0.8959	0.9465	-0.2883	2.6310
	Q11c	Understand	EoIAE3	1.309	1.056	1.028	-0.6240	3.7564
Ease of Complete Intelligibility	**Q**13b	Clear	EoCI1	1.140	1.277	1.130	-0.9208	3.8433
	Q13c	Comprehensible	EoCI2	1.3384	0.8593	0.9270	-0.7202	3.6182
	Q13d	Lucid	EoCI3	0.743	1.425	1.194	-0.7570	3.7845
Ease of Integrating	**Q**22a	Easily	EoI1	1.016	1.131	1.064	-0.8078	3.8479
	Q22b	Readily	EoI2	1.051	1.339	1.157	-1.1512	4.3701
Representational Faithfulness	**Q**14a	Phenomena	RF1	0.712	1.030	1.015	-0.3872	3.4881
	Q14b	Facts	RF2	1.1618	0.9162	0.9572	-0.8533	4.4507
	Q14c	Events	RF3	0.910	1.206	1.098	-0.9671	4.6697
Degree of Verification	**Q**15a	Substantiated	DoV1	0.578	1.905	1.380	-0.6380	3.4405
	Q15b	Verified	DoV2	0.587	1.831	1.353	-0.5401	3.6665
	Q15c	Checked	DoV3	0.863	1.642	1.281	-0.5635	3.7811
Neutrality	**Q**17a	Biased	Neu1	0.231	1.936	1.391	-0.1623	2.7405
	Q17b	Neutral	Neu2	0.626	1.533	1.238	0.0316	2.3704
Ease of Comparing	**Q**25	Easy	EoC1	1.207	1.052	1.025	-0.3327	3.8640
	Q26	Readily	EoC2	1.230	1.135	1.065	-0.1105	2.5678
	Q27	Facilitate	EoC3	1.5410	0.9903	0.9951	0.1156	1.9757
Relevance	**Q**9a	Bearing	Relev1	2.110	1.101	1.049	-1.6312	7.2273
	Q9b	Relevant	Relev2	2.0727	0.8094	0.8997	-1.2550	5.0204
	Q9c	Pertinent	Relev3	2.0673	0.8705	0.9330	-1.1454	4.3807
Reliability	**Q**30a	Dependable	Reli1	1.0693	0.7977	0.8931	-0.2482	2.5075
	Q30b	Reliable	Reli2	0.9032	0.9913	0.9957	-0.3628	2.2350
	Q30c	Trustworthy	Reli3	0.793	1.042	1.021	-0.4015	2.6534
	Q30d	Credible	Reli4	0.8508	0.8124	0.9013	-0.2248	2.1589
Sufficiency	**Q**34a	Adequately	Suf1	1.016	1.400	1.183	-0.8924	3.2738
	Q34b	Sufficiently	Suf2	0.710	1.392	1.180	-1.0252	3.9236
	Q34c	Satisfactorily	Suf3	0.668	1.328	1.152	-0.7233	2.7056
Satiation	**Q**29	Satiation	Sat1	-0.278	2.403	1.550	0.0824	3.2928
	Q32a	Comprehensive	Sat2	-0.294	1.962	1.401	-0.1984	3.6957
	Q32b	Complete	Sat3	-0.371	1.893	1.376	-0.1965	3.8364
Decision Usefulness	**Q**36h	Better	DU8	1.4521	0.7367	0.8583	-0.1642	2.4335
	Q36i	Improve	DU9	1.5836	0.5791	0.7610	-0.1823	2.8313
	Q36j	Increase	DU10	1.6076	0.6132	0.7831	-0.1451	2.7326

TABLE 2
INDICATOR TO LATENT VARIABLE LOADINGS AND CROSS-LOADINGS

	Latent Variables													
Indicators	Read	CwUAC	EoIAE	EoCI	EoI	RF	DoV	Neu	EoC	Relev	Reli	Suf	Sat	DU
Read1	**0.957**	0.523	0.582	0.625	0.275	0.481	0.088	0.155	0.420	0.393	0.310	0.277	0.180	0.491
Read2	**0.918**	0.540	0.463	0.514	0.191	0.435	0.083	0.075	0.444	0.406	0.350	0.346	0.118	0.426
Read3	**0.915**	0.523	0.524	0.679	0.101	0.552	0.077	0.125	0.341	0.343	0.284	0.255	0.145	0.594
CwUAC1	0.453	**0.824**	0.350	0.562	0.476	0.333	0.154	0.031	0.148	0.401	0.351	0.213	-0.066	0.226
CwUAC2	0.539	**0.819**	0.404	0.378	-0.029	0.197	0.273	-0.080	0.276	0.221	0.266	0.306	0.162	0.419
CwUAC3	0.421	**0.827**	0.365	0.415	0.077	0.387	0.161	-0.203	0.203	0.234	0.221	0.196	0.065	0.275
EoIAE1	0.464	0.407	**0.901**	0.334	0.066	0.609	0.257	0.178	0.355	0.394	0.390	0.406	0.165	0.293
EoIAE2	0.582	0.447	**0.973**	0.393	0.103	0.543	0.214	0.232	0.411	0.349	0.423	0.368	0.209	0.437
EoIAE3	0.540	0.410	**0.942**	0.401	0.270	0.359	0.254	0.307	0.473	0.415	0.424	0.453	0.212	0.491
EoCI1	0.610	0.497	0.262	**0.923**	0.508	0.331	-0.118	0.023	0.215	0.236	0.289	0.388	0.185	0.436
EoCI2	0.688	0.536	0.486	**0.887**	0.376	0.480	0.148	0.112	0.319	0.218	0.385	0.415	0.345	0.577
EoCI3	0.422	0.465	0.296	**0.855**	0.402	0.550	-0.047	-0.134	0.284	0.121	0.379	0.403	0.162	0.397
EoI1	0.196	0.222	0.167	0.479	**0.986**	0.070	0.067	0.033	0.199	0.228	0.246	0.149	-0.111	0.210
EoI2	0.192	0.308	0.136	0.441	**0.942**	0.160	-0.002	-0.111	0.100	0.291	0.146	0.057	-0.216	0.188
RF1	0.361	0.197	0.376	0.319	0.034	**0.872**	0.143	0.025	0.154	0.282	0.372	0.226	0.193	0.174
RF2	0.573	0.372	0.418	0.386	-0.077	**0.692**	0.018	0.093	0.208	0.363	0.328	0.183	0.320	0.393
RF3	0.319	0.311	0.425	0.455	0.249	**0.736**	0.182	-0.029	0.190	0.288	0.402	0.277	0.064	0.249
DoV1	-0.055	0.182	0.194	-0.090	0.104	0.161	**0.917**	0.115	0.157	0.157	0.328	0.143	-0.065	0.064
DoV2	0.061	0.149	0.196	-0.007	-0.012	0.172	**0.944**	0.117	0.218	0.037	0.263	0.103	0.045	0.082
DoV3	0.320	0.312	0.323	0.174	0.002	0.059	**0.768**	0.150	0.330	0.169	0.202	0.217	0.093	0.378
Neu1	-0.083	-0.296	0.109	-0.157	-0.040	-0.115	0.129	**0.908**	0.120	0.112	0.168	0.126	0.223	0.038
Neu2	0.308	0.123	0.355	0.173	0.010	0.167	0.127	**0.920**	0.180	0.376	0.260	0.256	0.148	0.178
EoC1	0.280	0.102	0.262	0.092	0.025	0.149	0.291	0.224	**0.762**	0.142	0.341	0.312	0.339	0.339
EoC2	0.342	0.187	0.421	0.176	0.104	0.358	0.299	0.048	**0.878**	0.091	0.466	0.244	0.161	0.469
EoC3	0.429	0.275	0.416	0.403	0.230	0.137	0.131	0.169	**0.910**	0.205	0.421	0.444	0.258	0.677
Relev1	0.285	0.100	0.262	-0.048	0.013	0.241	0.000	0.146	0.094	**0.591**	-0.037	-0.035	-0.064	0.091
Relev2	0.428	0.397	0.437	0.304	0.305	0.428	0.168	0.266	0.178	**0.972**	0.192	0.306	0.104	0.258
Relev3	0.348	0.352	0.356	0.191	0.244	0.353	0.125	0.269	0.178	**0.978**	0.174	0.314	0.045	0.257
Reli1	0.377	0.356	0.436	0.425	0.224	0.458	0.360	0.218	0.518	0.148	**0.938**	0.590	0.356	0.520
Reli2	0.339	0.367	0.454	0.420	0.174	0.484	0.298	0.241	0.472	0.220	**0.952**	0.617	0.500	0.438
Reli3	0.338	0.350	0.405	0.377	0.266	0.432	0.262	0.203	0.479	0.135	**0.945**	0.522	0.324	0.409
Reli4	0.137	0.183	0.307	0.189	0.133	0.399	0.193	0.209	0.260	0.083	**0.864**	0.386	0.303	0.243
Suf1	0.325	0.267	0.433	0.478	0.174	0.275	0.227	0.208	0.435	0.259	0.557	**0.947**	0.498	0.421
Suf2	0.287	0.294	0.434	0.440	0.096	0.275	0.139	0.199	0.368	0.241	0.553	**0.977**	0.601	0.305
Suf3	0.261	0.251	0.369	0.356	0.057	0.313	0.087	0.194	0.345	0.306	0.552	**0.932**	0.539	0.311
Sat1	0.197	0.024	0.156	0.284	-0.042	0.260	-0.077	0.171	0.250	0.100	0.374	0.569	**0.931**	0.123
Sat2	0.137	0.059	0.227	0.249	-0.187	0.219	0.045	0.185	0.283	0.046	0.377	0.528	**0.982**	0.163
Sat3	0.121	0.045	0.213	0.236	-0.211	0.199	0.082	0.240	0.275	0.008	0.432	0.534	**0.941**	0.080
DU8	0.474	0.330	0.451	0.547	0.215	0.365	0.216	0.172	0.664	0.174	0.542	0.436	0.213	**0.918**
DU9	0.586	0.406	0.458	0.552	0.249	0.415	0.232	0.114	0.615	0.266	0.494	0.313	0.104	**0.947**
DU10	0.535	0.386	0.497	0.509	0.218	0.372	0.243	0.170	0.672	0.353	0.467	0.385	0.116	**0.942**

Latent Variable Level Analyses. We assayed our measurement model at the LV level by testing LV reliability and convergent and discriminant validities. We used Werts, Linn, and Joreskog's (1974) composite reliability (CR) measure to test reliability (Chin, 1998).

Composite reliability is interpreted like Cronbach's alpha (Tavakol & Dennick, 2011). Alpha tends to be a lower-bound reliability estimate, while CR is more exacting if parameter estimates are accurate (Chin, 2010); CR's range is 0 (unreliable) to 1 (perfectly reliable). Respectively, CR thresholds for confirmatory and exploratory studies are 0.80 and 0.70 (Urbach & Ahlemann, 2010). Scores below 0.60 are unacceptable (Nunnally & Bernstein, 1994). Scores above 0.95 are questioned more than those near 0.60, as high scores suggest common method bias (Urbach & Ahlemann, 2010).

Table 3 shows CR scores in the 0.813 - 0.967 range. This is an exploratory study, yet our CR scores are higher than the confirmatory study threshold. Our scores for five LVs are slightly questionable: Ease of Interpreting Accounting Estimates (0.957), Ease of Integrating (0.963), Reliability (0.960), Sufficiency (0.967) and Satiation (0.966). Overall, our CR scores exhibit LV reliability.

To evaluate LV convergent validity, average variance extracted (AVE) is recommended (Chin, 1998). It measures the variance captured by the LV relative to measurement error variance. The AVE range is 0 (no convergence) to 1 (perfect convergence); the threshold is 0.50. If AVE is less than 0.50, the variance captured by the LV is less than measurement error variance, and indicator and LV validity are suspect (Fornell & Larcker, 1981).

Table 3 shows AVE on its diagonals; the AVE range is 0.594 - 0.929. Thus, all scores are higher than the AVE threshold and demonstrate convergent validity.

To evaluate LV discriminant validity the Fornell-Larcker criterion (Fornell & Larcker, 1981) is recommended. It compares AVE to the square of the correlations (variance) among the LVs. It specifies that a LV share more variance with its indicators than with any LV. Discriminant validity is exhibited if a LV's AVE is greater than its highest squared correlation with any LV (Chin, 1998, 2010).

Table 3 shows our Fornell-Larcker criterion data. For a given LV, its variances among the LVs are shown directly below and directly to the left of its AVE score. For each LV, the criterion is more than adequately met; discriminant validity is demonstrated.

Table 3 shows LV reliability and high construct and discriminant validities.

TABLE 3
SHARED VARIANCE AMONG LATENT VARIABLES (SQUARED CORRELATIONS), AVERAGE VARIANCE EXTRACTED, AND COMPOSITE RELIABILITY

Shared Variance Among Latent variables with Average Variance Extracted (on the diagonals)

Latent Variables	Read	CwUAC	EoIAE	EoCI	EoI	RF	DoV	Neu	EoC	Relev	Reli	Suf	Sat	DU
Read	**0.865**													
CwUAC	0.322	**0.678**												
EoIAE	0.320	0.202	**0.881**											
EoCI	0.435	0.319	0.162	**0.790**										
EoI	0.040	0.067	0.026	0.230	**0.929**									
RF	0.283	0.143	0.279	0.255	0.011	**0.594**								
DoV	0.008	0.053	0.066	0.000	0.002	0.024	**0.774**							
Neu	0.017	0.008	0.067	0.000	0.000	0.001	0.020	**0.836**						
EoC	0.182	0.059	0.196	0.095	0.029	0.057	0.062	0.027	**0.726**					
Relev	0.165	0.132	0.168	0.049	0.066	0.161	0.018	0.074	0.032	**0.750**				
Reli	0.112	0.122	0.193	0.156	0.048	0.232	0.095	0.055	0.231	0.027	**0.856**			
Suf	0.096	0.081	0.190	0.205	0.015	0.091	0.028	0.045	0.166	0.079	0.340	**0.907**		
Sat	0.026	0.002	0.044	0.073	0.023	0.057	0.000	0.041	0.080	0.003	0.165	0.323	**0.905**	
DU	0.302	0.128	0.193	0.290	0.044	0.120	0.028	0.015	0.389	0.064	0.202	0.138	0.019	**0.708**
Composite Reliability	0.951	0.864	0.957	0.919	0.963	0.813	0.911	0.911	0.888	0.896	0.960	0.967	0.966	0.935

Structural Model

After establishing our measurement model's validity, we assessed our structural model. Usually two measures are used to assay PLS structural models: coefficient of determination (R^2) and path coefficients. A third is advocated, but rarely reported: effect size (Chin, 1998, 2010). We used each of these.

Coefficient of Determination. The size of a dependent LV's explained variance relative to its total variance is captured by R^2. Therefore, R^2 measures a model's predictive ability. Respectively, values of approximately 0.670, 0.333, and 0.190 should be considered substantial, average, and weak (Chin, 1998).

Figure 3 shows our structural model results and depicts four dependent LVs. Explained variance is average to substantial for two: Decision Usefulness (R^2=0.526) and Ease of Complete Intelligibility (R^2=0.489). The variance is average for Reliability (R^2=0.321); yet it is not even weak for Ease of Comparing (R^2=0.096). Decision Usefulness is our primary predictor; given its R^2, our structural model exhibits predictive ability.

Path Coefficients. A path coefficient connects two LVs, measures the relationship between them and represents an implicit hypothesis. Algebraic sign, size and significance are used to assess a coefficient. Its sign is a relationship direction measure (direct versus inverse); it should correspond with the theorized relationship. Size is a relationship strength measure; some maintain coefficients should exceed 0.10 (Urbach & Ahlemann, 2010). Significance is measured using bootstrapping[7] [8]. Urbach and Ahlemann (2010) suggest setting the significance level at 0.05. Our study is exploratory; therefore, we employed a < 0.10 level.

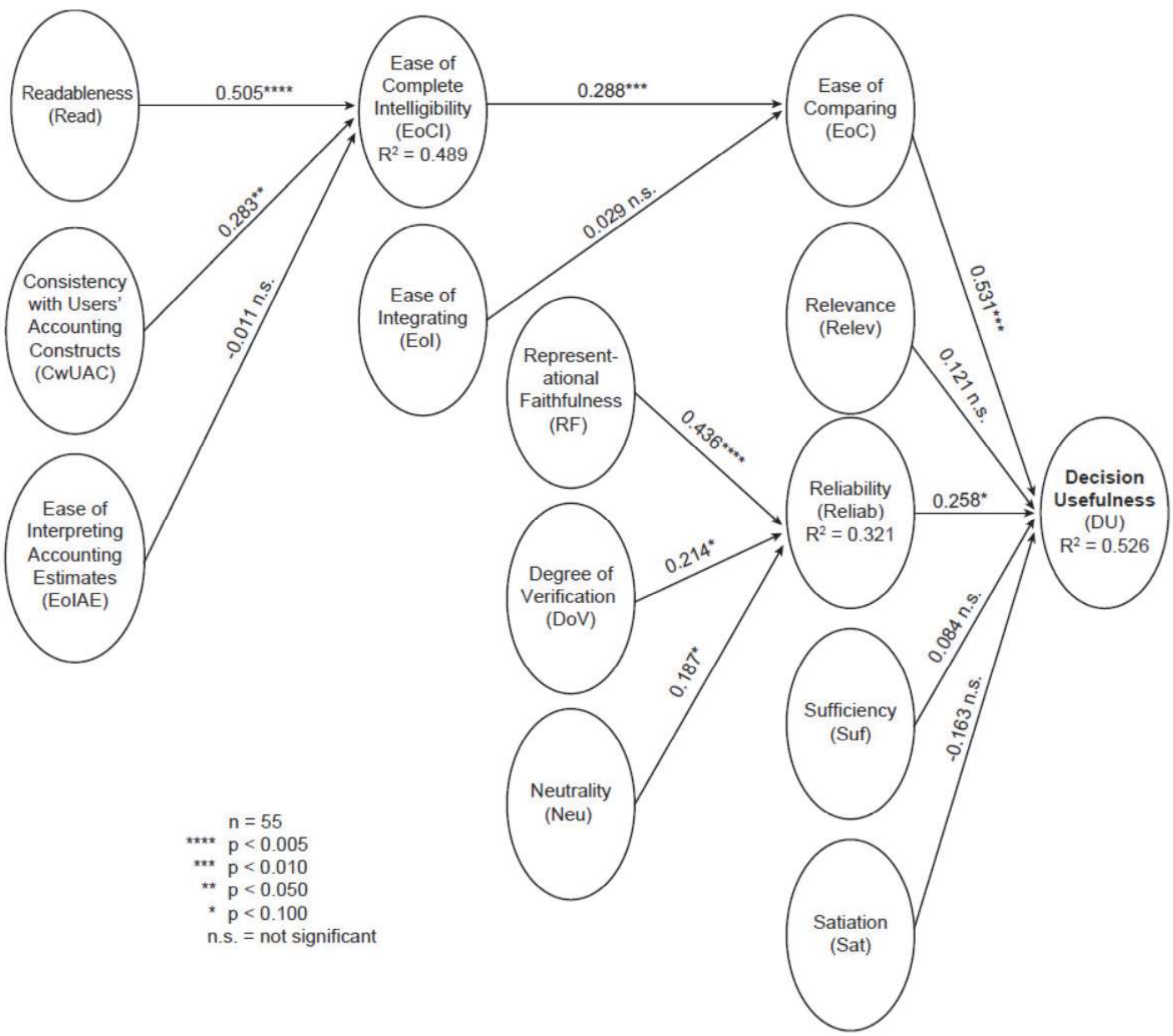
Figure 3 shows 13 path coefficients; eight meet the coefficient evaluation criteria. Thus, there is a positive statistically significant relationship between the correspondent LVs. One coefficient (Relevance → Decision Usefulness) has the theorized sign and meets the size threshold, but is not statistically significant. This indicates a positive relationship between the LVs, albeit not a statistically significant one. Another coefficient (Sufficiency → Decision Usefulness), has the theorized sign, a size less than the threshold and is not statistically significant. This indicates an direct relationship between the LVs, but not a statistically significant one. Yet another coefficient (Satiation → Decision Usefulness), has a sign that differs from that theorized, a size exceeding the threshold and is not statistically significant. This indicates an inverse relationship between the LVs, but not a statistically significant one. Another coefficient (Ease of Integrating → Ease of Comparing) has the theorized sign, a size less than the threshold, but is not statistically significant. This indicates a weak positive non-statistically significant relationship between the LVs. The last coefficient (Ease of Interpreting Accounting Estimates → Ease of Complete Intelligibility), does not meet any criterion, suggesting there is no relationship between the LVs.

In summary, Figure 3 shows most path coefficients support our theorized relationships. However, several coefficients are not statistically significant, two convey an inverse relationship rather than the theorized direct relationship, and one conveys no relationship.

Effect Size. Effect size estimates the strength of the structural model findings by measuring the magnitude and direction of the relationship between two LVs. This information is not provided by simply examining a path coefficient's statistical significance because there is no direct relationship between a p-value and effect size magnitude. Hence, a small p-value can occur with a small, medium, or large effect size. Further, there is no direct relationship between effect size and practical significance. Depending on the study, a small effect may be more important to the empirical outcome than a large one (Durlak, 2009).

Chin (1998, 2010) asserts that effect size is measured as the magnitude of change in the predictor LV's R^2 resulting from excluding an antecedent. Effect size can be evaluated similar to Cohen's (1992) f^2 values. Respectively, small, medium, and large effect sizes are revealed by R^2 magnitude changes of 0.02, 0.15, and 0.35 (Chin, 1998; Cohen, 1992).

FIGURE 3
STRUCTURAL MODEL



Five antecedent LVs predict Decision Usefulness: Ease of Comparing, Relevance, Reliability, Sufficiency, and Satiation. Respectively, these are their effect sizes: 0.441, 0.027, 0.080, 0.008, and 0.038. The effect size of Ease of Comparing is very large; that of Reliability is small to medium; and those of Relevance and of Satiation are small. However, the Sufficiency effect size is minuscule. Table 4 summarizes these results.

In summary, Decision Usefulness, our primary predictor LV has an average to substantial R^2. Hence, our structural model exhibits more than adequate explained variation and thus has predictive ability. Most path coefficients support our theorized direct relationships. However, several coefficients are not statistically significant and two convey an inverse relationship. Our effect size results range from miniscule to very large.

TABLE 4
STRUCTURAL MODEL EFFECT SIZES

Latent Variable Names	R^2 if Included	R^2 if Excluded	f^2 Effect Size	Practical Effect	Corresponding Cohen's f^2 Values
Ease of Comparing	0.526	0.317	0.441	Very Large	≥ 0.35
Relevance	0.526	0.513	0.027	Small	0.02
Reliability	0.526	0.488	0.080	Small to Medium	0.02 – 0.15
Sufficiency	0.526	0.522	0.008	Nil	<0.02
Satiation	0.526	0.508	0.038	Small	0.02

SUMMARY AND CONCLUSIONS

Professional investors persistently express discontent with segment data decision usefulness. To enhance their decision-making, they have repeatedly requested that standard-setters require the disclosure of more decision-useful data. They suggest their decision-making would be improved if these were disclosed by segment: cash flow, gross margin and working capital. Given the level of interest that investors have in segment data, exploring a method for objectively assessing its decision usefulness is overdue. Thus, we undertook this two-phased mixed-methods study to explore data qualities that compose the SDDPM, a model that facilitates the assessment of segment data decision usefulness.

In the first phase, we developed SDDPM data quality measures and our questionnaire. In the second, we surveyed fundamental-equity investors, the investors most interested in segment data (Tollerson et al., 2015). Further, we used PLS to explore the SDDPM at the measurement and structural model levels.

For our measurement model, we have two findings. First, at the indicator level, our measures exhibit high item reliability and high convergent and discriminant validities. Second, at the LV level, the question set for each LV exhibits reliability and high construct discriminant validities. Thus, our questions reliably measure the intended data qualities.

Our most significant findings concern our structural model, which we assessed in terms of its R^2, path coefficients and effect sizes. The SDDPM has predictive ability, as Decision Usefulness (the primary predictor) has a R^2 in the average to substantial range. Most of our thirteen path coefficients support our theorized relationships. However, three are not statistically significant, two convey an inverse rather than direct relationship, and one conveys no relationship. Concerning effect size, of the five direct antecedents of Decision Usefulness, Ease of Comparing has the strongest effect, followed by Reliability, Relevance, and Sufficiency. Satiation, however, has a small inverse effect.

Our study is exploratory as the SDDPM is emerging and our attained sample size is small. Exploring the SDDPM demonstrates its utility. We make no claims about investors' decision-usefulness perceptions; that issue we leave to others. Even so, we created new measures; measure utility increases with effective use. Our findings suggest the measures could be useful to future researchers.

Future segment data researchers, PIR review teams, or both should replicate our study with a larger sample. Doing so would allow them to examine investors' perceptions. A larger sample would facilitate robustly and objectively examining, in the context of segment reporting, the indirect relationships among Relevance, Reliability and Decision Usefulness. Such an examination will shed light on the more general questions of whether Relevance and Reliability conflict, and which has a greater influenced on perceived decision usefulness. Standard-setters in accounting are keen to see these questions explored (Barth, 2006).

ENDNOTES

1. The FAF's trustees have oversight responsibility for the Financial Accounting Standards Board (FASB). They direct the FAF staff to form PIR teams and conduct PIR's. One PIR objective is to determine if the FASB's standards are meeting their stated purposes. These assessments are made by evaluating issues such as whether firms' disclosures are decision-useful (FAF, 2015).
2. Tollerson, Chin, and Gamble (2015) put forward a general and a segment data decision-usefulness prediction model. They did not name the latter, however, to ease composition we named it.
3. The SDDPM's data quality (latent variable) definitions are presented in Appendix A Table 1.
4. Tollerson et al. (2015) developed the SDDPM before Statement of Financial Accounting Concepts (SFAC No. 8), "Conceptual Framework for Financial Reporting" (FASB, 2010), was issued. SFAC No. 8 sets forth the FASB's latest data qualities and is similar to SFAC No. 2, "Qualitative Characteristics of Accounting Information", (FASB, 1980), which they employed.
5. The fundamental analysis decision model focuses users' attention on understanding firms and factors that affect them. Discounted cash flow techniques are employed to devise long-term firm-specific market valuations (Damodaran, 2002).
6. We employed e-mail survey response data, because comparable mail data were not available.
7. Chin (1998) first advocated bootstrapping to measure coefficient statistical significance. Bootstrapping estimates PLS estimate precision; N sample sets are formed to obtain N estimates for each model parameter. Each sample is created by sampling with replacement from the empirical data set, until the number of cases agrees with that of the data set (Chin, 2010).
8. We used PLS-Graph's distribution free percentile approach for bootstrapping. We set N=1000.

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APPENDICES

APPENDIX A
SDDPM's LATENT VARIABLE DEFINITIONS

TABLE A1
DECISION USEFULNESS AND ITS ANTECEDENT LATENT VARIABLE DEFINITIONS - SEGMENT DISCLOSURES

Latent variables	Definitions- Segment disclosures
Decision Usefulness	Decision usefulness is the quality of segment disclosures that represents a judgment deduced by fundamental-equity investors to assess whether segment disclosures improve their understandings of firms.
Ease of Comparing	Ease of comparing is the quality of segment disclosures that represents the extent to which fundamental-equity investors perceive that segment disclosures make their comparisons easy.
Relevance	Relevance is the quality of segment disclosures that represents the extent to which fundamental-equity investors perceive that segment disclosures are relevant to their knowledge of firms.
Reliability	Reliability is the quality of segment disclosures that represents the extent to which fundamental-equity investors perceive that segment disclosures are dependable in improving their understandings of firms.
Sufficiency	Sufficiency is the quality of segment disclosures that represents the extent to which fundamental-equity investors perceive that segment disclosures provide adequate reported segment disclosures for improving their understandings of firms.
Satiation	Satiation is the quality of segment disclosures that represents the extent to which fundamental-equity investors perceive that segment disclosures reveal all the segment disclosures they desire for improving their understandings of firms.

Note. Source: Tollerson, Chin, and Gamble (2015). Reproduced with permission.

TABLE A2
EASE OF COMPARING ANTECEDENT LATENT VARIABLE DEFINITIONS - SEGMENT DISCLOSURES

Latent variables	Definitions- Segment disclosures
Ease of Complete Intelligibility	Ease of complete intelligibility is the quality of segment disclosures that represents the extent to which fundamental-equity investors perceive that segment disclosures are lucid.
Ease of Integrating	Ease of integrating is the quality of segment disclosures that represents the extent to which fundamental-equity investors perceive that segment disclosures are easy to integrate into their system (fundamental analysis decision model) of understanding firms.

Note. Source: Tollerson, Chin, and Gamble (2015). Reproduced with permission.

TABLE A3
EASE OF COMPLETE INTELLIGIBILITY ANTECEDENT LATENT VARIABLE DEFINITIONS – SEGMENT DISCLOSURES

Latent variables	Definitions- Segment disclosures
Readableness	Readableness is the quality of segment disclosures that represents the extent to which fundamental-equity investors perceive that segment disclosures are easy to read.
Consistency with Users' Constructs	Consistency with users' accounting constructs is the quality of segment disclosures that represents the extent to which fundamental-equity investors perceive that segment disclosure accounting concepts are equivalent in function to their own accounting concepts.
Ease of Interpreting Estimates	Ease of interpreting accounting estimates is the quality of segment disclosures that represents the extent to which fundamental-equity investors perceive that segment disclosure accounting estimates are easy to interpret.

Note. Source: Tollerson, Chin, and Gamble (2015). Reproduced with permission.

TABLE A4
RELIABILITY ANTECEDENT LATENT VARIABLE
DEFINITIONS – SEGMENT DISCLOSURES

Latent variables	Definitions- Segment disclosures
Representational Faithfulness	Representational faithfulness is the quality of segment disclosures that represents the extent to which fundamental-equity investors perceive that segment disclosures correspond with the phenomenon the disclosures claim to describe.
Degree of Verification	Degree of verification is the quality of segment disclosures that represents the extent to which fundamental-equity investors perceive that segment disclosures are supported by adequate verified evidence.
Neutrality	Neutrality is the quality of segment disclosures that represents the extent to which fundamental-equity investors perceive that segment disclosures are not unreasonably supportive of a particular position in the segment reporting disclosure debate.

Note. Source: Tollerson, Chin, and Gamble (2015). Reproduced with permission.

APPENDIX B

OPERATIONALIZED SDDPM LATENT VARIABLE DEFINITIONS AND CORRESPONDING QUESTIONNAIRE QUESTIONS, INDICATORS, AND SCALE DESCRIPTIONS

TABLE B1
DECISION USEFULNESS CONSTRUCT: DEFINITION AND POST-1998 MEASUREMENT MODEL INDICATORS, AND QUESTIONNAIRE QUESTIONS AND SCALE DESCRIPTION

Definition	Decision usefulness is a judgment deduced by fundamental-equity investment professionals to assess whether reported products and services segment disclosures improve their understandings of firms	
		Scale Description
Indicators	Q36. Post-1998 reported segment disclosures ______________ my understanding of firms.	Likert, 7 point, -3 to +3, Strongly Agree to Strongly Disagree
DU8	Q36h. better	
DU9	Q36i. improve	
DU10	Q36. increase	

TABLE B2
EASE OF COMPARING CONSTRUCT: DEFINITION AND POST-1998 MEASUREMENT MODEL INDICTORS AND QUESTIONNAIRE QUESTIONS AND SCALE DESCRIPTION

Definition	Ease of comparing is the extent to which fundamental-equity investment professionals perceive that reported products and services segment disclosures make their comparisons easy.	
		Scale Description
Indicators		Likert, 7 point, -3 to +3, Strongly Agree to Strongly Disagree
EoC1	Q25. Post-1998 reported segment disclosures are easy for me to compare.	
EoC2	Q26. I readily compare post-1998 reported segment disclosures.	
EoC3	Q27. Post-1998 reported segment disclosures facilitate my comparisons.	

TABLE B3
RELEVANCE CONSTRUCT: DEFINITION AND POST-1998 MEASUREMENT MODEL INDICATORS, AND QUESTIONNAIRE QUESTIONS AND SCALE DESCRIPTION

Definition	Relevance is the extent to which fundamental-equity investment professionals perceive that reported products and services segment disclosures have a bearing on their knowledge of firms.	
		Scale Description
Indicators	Q9 I believe post-1998 reported segment disclosures _________ my knowledge of firms.	Likert, 7 point, -3 to +3, Strongly Agree to Strongly Disagree
Relev1	Q9a.have a bearing on	
Relev2	Q9b. are relevant to	
Relev3	Q9c.are pertinent to	

TABLE B4
RELIABILITY CONSTRUCT: DEFINITION AND POST-1998 MEASUREMENT MODEL INDICTORS, AND QUESTIONNAIRE QUESTIONS AND SCALE DESCRIPTION

Definition	Reliability is the extent to which fundamental-equity investment professionals perceive that reported products and services segment disclosures are suitable to depend on to improve their understandings of firms.	
		Scale Description
Indicators	Q30. Post-1998 reported segment disclosures are __________ for improving my understanding of firms.	Likert, 7 point, -3 to +3, Strongly Agree to Strongly Disagree
Reli1	Q30a. dependable	
Reli2	Q30b. reliable	
Reli3	Q30c. trustworthy	
Reli4	Q30d. credible	

TABLE B5
SUFFICIENCY CONSTRUCT: DEFINITION AND POST-1998 MEASUREMENT MODEL INDICATORS, AND QUESTIONNAIRE QUESTIONS AND SCALE DESCRIPTION

Definition	Sufficiency is the extent to which fundamental-equity investment professionals perceive that reported products and services segment disclosures provide adequate reported segment disclosures for improving their understandings of firms.	
		Scale Description
Indicators	Q34. Post-1998 reported segment disclosures ___________ meet my minimum requirements for improving my understanding of firms.	Likert, 7 point, -3 to +3, Strongly Agree to Strongly Disagree
Suf1	Q34a. adequately	
Suf2	Q34b. sufficiently	
Suf3	Q34c. satisfactorily	

TABLE B6
SATIATION CONSTRUCT: DEFINITION AND POST-1998 MEASUREMENT MODEL INDICATORS, AND QUESTIONNAIRE QUESTIONS AND SCALE DESCRIPTION

Definition	Satiation is the extent to which fundamental-equity investment professionals perceive that reported products and services segment disclosures reveal all the reported segment disclosures they desire for improving their understandings of firms.
Indicators	Nine Point Semantic Differential Scale Questions
Sat1	Q29. For improving my understanding of firms, post-1998 reported segment disclosures are_________ what I want. far less than -4 -3 -2 -1 0 (about) 1 2 3 4 far more than
	Q32. For improving my understanding of firms, post-1998 reported segment disclosures are_________ what I desire.
Sat2	Q32a. far less comprehensive than -4 -3 -2 -1 0 (about) 1 2 3 4 far more comprehensive than
Sat3	Q32b. far less comprehensive than -4 -3 -2 -1 0 (about) 1 2 3 4 far more comprehensive than

TABLE B7
EASE OF COMPLETE INTELLIGIBILITY CONSTRUCT: DEFINITION, POST-1998 MEASUREMENT MODEL INDICATORS, AND QUESTIONNAIRE QUESTIONS AND SCALE DESCRIPTION

Definition	Ease of complete intelligibility is the extent to which fundamental-equity investment professionals perceive that reported products and services segment disclosures are lucid.	
		Scale Description
Indicators	Q13. For me, post-1998 reported segment disclosures are ______.	Likert, 7 point, -3 to +3, Strongly Agree to Strongly Disagree
EoCI1	Q13b. clear	
EoCI2	Q13c. comprehensible	
EoCI3	Q13d. lucid	

TABLE B8
EASE OF INTEGRATING CONSTRUCT: DEFINITION, POST-1998 MEASUREMENT MODEL INDICATORS, AND QUESTIONNAIRE QUESTIONS AND SCALE DESCRIPTION

Definition	Ease of integrating is the extent to which fundamental-equity investment professionals perceive that reported products and services segment disclosures are easy to integrate into their system of understanding firms.	
		Scale Description
Indicators	Q22. I _____________ incorporate post-1998 reported segment disclosures into my procedures for analyzing disclosures.	Likert, 7 point, -3 to +3, Strongly Agree to Strongly Disagree
EoI1	Q22a. easily	
EoI2	Q22b. readily	

TABLE B9
READABLENESS CONSTRUCT: DEFINITION, POST-1998 MEASUREMENT MODEL INDICATORS, AND QUESTIONNAIRE QUESTIONS AND SCALE DESCRIPTION

Definition	Readableness is the extent to which fundamental-equity investment professionals perceive that reported products and services segment disclosures are easy for them to read.	
		Scale Description
Indicators	Q12. I ___________ read post-1998 reported segment disclosures.	Likert, 7 point, -3 to +3, Strongly Agree to Strongly Disagree
Read1	Q12a. easily	
Read2	Q12b. readily	
		Scale Description
	Q13. For me, post-1998 reported segment disclosures are _____.	Likert, 7 point, -3 to +3, Strongly Agree to Strongly Disagree
Read3	Q13a. readable	

TABLE B10
CONSISTENCY WITH USERS' ACCOUNTING CONSTRUCTS CONSTRUCT: DEFINITION, POST-1998 MEASUREMENT MODEL INDICATORS, AND QUESTIONNAIRE QUESTIONS AND SCALE DESCRIPTION

Definition	Consistency with users' accounting constructs is the extent to which fundamental-equity investment professionals perceive that reported products and services segment disclosure accounting concepts are equivalent in function to their accounting concepts.	
		Scale Description
Indicators	Q10. I believe the accounting concepts used to determine post- 1998 reported segment disclosures are _______ to my accounting concepts. These concepts focus on how firms determine their reported segments and what they report about them.	Likert, 7 point, -3 to +3, Strongly Agree to Strongly Disagree
CwUAC1	Q10a. equivalent in function	
CwUAC2	Q10b. similar	
CwUAC3	Q10c. analogous	

TABLE B11
EASE OF INTERPRETING ACCOUNTING ESTIMATES CONSTRUCT: DEFINITION, POST-1998 MEASUREMENT MODEL INDICATORS, AND QUESTIONNAIRE QUESTIONS AND SCALE DESCRIPTION

Definition	Ease of interpreting accounting estimates is the extent to which fundamental-equity investment professionals perceive that reported products and services segment disclosure accounting estimates are easy for them to interpret.	
		Scale Description
Indicators	Q11. For me, post-1998 reported segment disclosure accounting estimates are easy to ________.	Likert, 7 point, -3 to +3, Strongly Agree to Strongly Disagree
EoIAE1	Q11a. interpret	
EoIAE2	Q11b. comprehend	
EoIAE3	Q11c. understand	

TABLE B12
REPRESENTATIONAL FAITHFULNESS CONSTRUCT: DEFINITION AND POST-1998 MEASUREMENT MODEL INDICATORS, AND QUESTIONNAIRE QUESTIONS AND SCALE DESCRIPTION

Definition	Representational faithfulness is the extent to which fundamental-equity investment professionals perceive that reported products and services segment disclosures correspond with the phenomenon the disclosures claim to describe.	
		Scale Description
Indicators	Q14. I believe post-1998 reported segment disclosures correspond with the segment _________________ they claim to describe.	Likert, 7 point, -3 to +3, Strongly Agree to Strongly Disagree
RF1	Q14a. phenomena	
RF2	Q14b. facts	
RF3	Q14c. events	

TABLE B13
DEGREE OF VERIFICATION CONSTRUCT: DEFINITION AND POST-1998 MEASUREMENT MODEL INDICATORS, AND QUESTIONNAIRE QUESTIONS AND SCALE DESCRIPTION

Definition	Degree of verification is the extent to which fundamental-equity investment professionals perceive that reported products and services segment disclosures are supported by adequate evidence.	
		Scale Description
Indicators	Q15. I believe post-1998 reported segment disclosures are ______ by firms' independent auditors.	Likert, 7 point, -3 to +3, Strongly Agree to Strongly Disagree
DoV1	Q15a. substantiated	
DoV2	Q15b. verified	
DoV3	Q15c. checked	

TABLE B14
NEUTRALITY CONSTRUCT: DEFINITION AND POST-1998 MEASUREMENT MODEL INDICATORS, AND QUESTIONNAIRE QUESTIONS AND SCALE DESCRIPTION

Definition	Neutrality is the extent to which fundamental-equity investment professionals perceive that reported products and services segment disclosures are not unduly supportive of a particular position in the segment reporting disclosure debate.	
		Scale Description
Indicators	Q17. I believe post-1998 reported segment disclosures are _____.	Likert, 7 point, -3 to +3, Strongly Agree to Strongly Disagree
Neu1	Q17a. biased	
Neu2	Q17b. neutral	