MIS Quarterly

RESEARCH ARTICLE

EXPECTATION CONFIRMATION IN INFORMATION SYSTEMS RESEARCH: A TEST OF SIX COMPETING MODELS

Susan A. Brown
Management Information Systems Department, Eller College of Management, University of Arizona,
Tucson, AZ 85721 U.S.A. {suebrown@eller.arizona.edu}

Viswanath Venkatesh
Walton College of Business, University of Arkansas
Fayetteville, AR 72701 U.S.A. {vvenkatesh@vvenkatesh.us}

Sandeep Goyal
College of Business, University of Louisville,
Louisville, KY 40292 U.S.A. {sandeep.goyal@louisville.edu}

Appendix A

Studies Using Polynomial Modeling in Information Systems Reference Fields

Paper Reference	Discipline	Theory
Atwater et al. (1998)	Personnel Psychology	Self-other agreement
Bailey and Fletcher (2002)	Organizational Behavior	Management competence
Brown et al. (2012)	Information Systems	Expectation confirmation
Brown et al. (2008)	Organizational Behavior	Expectation confirmation
Bono and Colbert (2005)	Psychology	Job performance
Dineen et al. (2005)	Management	Integrative theory
Edwards (1994)	Organizational Behavior	Person-environment fit
Edwards and Cable (2009)	Psychology	Person-environment fit
Edwards and Harrison (1993)	Management	Person-environment fit
Edwards and Parry (1993)	Management	Person-environment fit
Edwards and Rothbard (1999)	Organizational Behavior	Person-environment fit
Hetch and Allen (2005)	Organizational Behavior	Person-job fit
Hom et al. (1999)	Personnel Psychology	Realistic job preview
Irving and Meyer (1994)	Psychology	Met expectations hypothesis
Irving and Meyer (1995)	Personnel Psychology	Met expectations hypothesis
Irving and Meyer (1999)	Personnel Psychology	Met expectations hypothesis
Kim and Hsieh (2003)	Marketing	Distributor-supplier relationships
Klein et al. (2009)	Information Systems	IS service quality

Paper Reference	Discipline	Theory
Kreiner (2006)	Organizational Behavior	Person-environment fit
Kristof-Brown and Guay (2010)	Psychology	Person-environment fit
Kristoff-Brown and Stevens (2001)	Psychology	Person-environment fit
Lambert et al. (2003)	Personnel Psychology	Psychological contract theory
Lubatkin et al. (2006)	Management	Behavioral integration
Oh and Pinsonneault (2007)	Information Systems	Resource-centered and contingency-based view
Shaw and Gupta (2004)	Personnel Psychology	Person-environment fit
Titah and Barki (2009)	Information Systems	Economic theory of complementarities
Venkatesh and Goyal (2010)	Information Systems	Expectation confirmation
Yi (1990)	Marketing	Expectation confirmation

References

Atwater, L. E., Ostroff, C., Yammarino, F. J., and Fleenor, J. W. 1998. "Self-Other Agreement: Does It Really Matter?," *Personnel Psychology* (51:3), pp. 577-598.

Bailey, X., and Fletcher, C. 2002. "The Impact of Multiple Source Feedback on Management Development: Findings from a Longitudinal Study," *Journal of Organizational Behavior* (23), pp. 853-867.

Bono, J. E., and Colbert, A. E. 2005. "Understanding Responses to Multi-Source Feedback: The Role of Core Self-Evaluations," *Personnel Psychology* (58), pp. 171-203.

Brown, S. A., Venkatesh, V., and Goyal. S. 2012. "Expectation Confirmation in Technology Use," *Information Systems Research* (23:2), pp. 474-487.

Brown, S. A., Venkatesh, V., Kuruzovich, J. N., and Massey, A. P. 2008. "Expectation Confirmation: An Examination of Three Competing Models," *Organizational Behavior and Human Decision Processes* (105:1), pp. 52-66.

Dineen, B. R., Van de Walle, D., and Noe, R. A. 2005. "Job Seeker Goal Orientation and the Relative Weighing of P-O and Demands-Abilities Fit Perceptions in Making Applicant Decisions," in *Proceedings of the 20th Annual Meeting of the Society for Industrial and Organizational Psychology*, Los Angeles, CA.

Edwards, J. R. 1994. "Regression Analysis as an Alternative to Difference Scores," *Journal of Management* (20:3), pp. 683-689.

Edwards, J. R. 2002. "Alternatives to Difference Scores: Polynomial Regression Analysis and Response Surface Methodology," in *Measuring and Analyzing Behavior in Organizations: Advances in Measurement and Data Analysis,* F. Drasgow and N. Schmidt (eds.), San Francisco: Jossey-Bass/Pfeiffer, pp. 350-400.

Edwards, J. R., and Harrison, R. V. 1993. "Job Demands and Worker Health: Three-Dimensional Reexamination of the Relationship between Person–Environment Fit and Strain," *Journal of Applied Psychology* (78:4), pp. 628-648.

Edwards, J. R., and Parry, M. E. 1993. "On the Use of Polynomial Regression Equations as an Alternative to Difference Scores in Organizational Research," *Academy of Management Journal* (36:6), pp. 1577-1613.

Edwards, J. R., and Rothbard, N. P. 1999. "Work and Family Stress and Well-Being: An Examination of Person–Environment Fit in the Work and Family Domains," *Organizational Behavior and Human Decision Processes* (77:2), pp. 85-129.

Hetch, T. D., and Allen, N. J. 2005. "Exploring Links between Polychronicity and Well-Being from the Perspective of Person-Job Fit: Does it Matter if You Prefer to Do Only One Thing at a Time?" *Organizational Behavior and Human Decision Processes* (98:2), pp. 155-178.

Hom, P. W., Griffeth, R. W., Palich, L. E., and Bracker, J. S. 1999. "Revisiting Met Expectations as a Reason Why Realistic Job Previews Work," *Personnel Psychology* (52:1), pp. 97-112.

Irving, P. G., and Meyer, J. P. 1995. "On Using Direct Measures of Met Expectations: A Methodological Note," *Journal of Management* (21:6), pp. 1159-1175.

Irving, P. G., and Meyer, J. P. 1999. "On Using Residual Difference Scores in the Measurement of Congruence: The Case of Met Expectations Research," *Personnel Psychology* (52:1), pp. 85-86.

Kim, S. K., and Hsieh, P. H. 2003. "Interdependence and its Consequences in Distributor–Supplier Relationships: A Distributor Perspective through Response Surface Approach," *Journal of Marketing Research* (40:1), pp. 101-112.

Klein, G., Jiang, J. J., and Cheney, P. 2009. "Resolving Difference Score Issues in Information Systems Research," *MIS Quarterly* (33:4), pp. 811-826.

Kreiner, G. E. 2006. "Consequences of Work-Home Segmentation or Integration: A Person–Environment Fit Perspective," *Journal of Organizational Behavior* (27), pp. 485-507.

Kristof-Brown, A. L., and Guay, R. P. 2010. "Person–Environment Fit," in *APA Handbook of Industrial and Organizational Psychology, Volume 3*, S. Zedeck (eds.), Washington, DC: American Psychological Association, pp. 3-50.

Kristof-Brown, A. L., and Stevens, C. 2001. "Goal Congruence in Project Teams: Does the Fit between Members' Personal Mastery and Performance Goals Matter?," *Journal of Applied Psychology* (86:6), pp. 1083-1095.
Lambert, L. S., Edwards, J. R., and Cable, D. M. 2003. "Breach and Fulfillment of the Psychological Contract: A Comparison of Traditional and Expanded Views," *Personnel Psychology* (56:4), pp. 895-935.
Lubatkin, M. H., Simsek, Z., Ling, Y. and Veiga, J. F. 2006. "Ambidexterity and Performance in Small- to Medium-Sized Firms: The Pivotal Role of Top Management Team Behavioral Integration," *Journal of Management* (32:5), pp. 646-672.
Oh, W., and Pinsonneault, A. 2007. "On the Assessment of the Strategic Value of Information Technologies: Conceptual and Analytic Approaches," *MIS Quarterly* (31:2), pp. 239-265.
Shaw, J. D., and Gupta, N. 2004. "Job Complexity, Performance, and Well-Being: When Does Supplies–Values Fit Matter?," *Personnel Psychology* (57), pp. 847-879.
Titah, R., and Barki, H. 2009. "Nonlinearities between Attitude and Subjective Norms in Information Technology Acceptance: A Negative Synergy?," *MIS Quarterly* (33:4), pp. 827-844.
Venkatesh, V., and Goyal, S. 2010. "Expectation Disconfirmation and Technology Adoption: Polynomial Modeling and Response Surface Analysis," *MIS Quarterly* (34:2), pp. 281-303.
Yi, Y. 1990. *A Critical Review of Consumer Satisfaction*, Chicago: American Marketing Association.

Appendix B

Items

All items were measured using a seven-point Likert scale with the endpoints strongly disagree to strongly agree, unless noted otherwise.

Expectation Items

Usefulness

I expect that <system> will enable me to accomplish tasks more quickly.
I expect that <system> will improve the quality of the work I do.
I expect that <system> will make it easier to do my job.
I expect that <system> will enhance my effectiveness on the job.
I expect that <system> will give me greater control over my job.
I expect that <system> will improve my productivity.

Ease of Use

I expect that it will be easy to get <system> to do what I want it to do.
I expect that overall,<system> will be easy to use.
I expect that learning to operate <system> will be easy for me.
I expect that interacting with <system> will not require a lot of my mental effort.

Experience Items

Usefulness

<system> enables me to accomplish tasks more quickly.
<system> improves the quality of the work I do.
<system> makes it easier to do my job.
<system> enhances my effectiveness on the job.
<system> gives me greater control over my job.
<system> improves my productivity.

Ease of Use

It is easy to get <system> to do what I want it to do.
Overall, <system> is easy to use.
Learning to operate <system> is easy for me.
Interacting with <system> does not require a lot of my mental effort.

Satisfaction
I am an enthusiastic user of <system>.
All things considered, my continuing to use <system> in my job is . . . (Extremely Negative to Extremely Positive).
All things considered, my continuing to use <system> in my job is . . . (Extremely Bad to Extremely Good)
All things considered, my continuing to use <system> in my job is . . . (Extremely Harmful to Extremely Beneficial).

Behavioral Intention
I intend to continue using the <system>.
I predict I would continue using the <system>.
I plan to continue using the <system>.

Disconfirmation Items

Usefulness
Compared to my initial expectations, the ability of <system>:
To improve my performance was (much worse than expected … much better than expected).
To increase my productivity was (much worse than expected … much better than expected).
To enhance my effectiveness was (much worse than expected … much better than expected).

Ease of Use
Compared to my initial expectations:
It was easy to get <system> to do what I want it to do (much worse than expected … much better than expected).
Overall, <system> was easy to use (much worse than expected … much better than expected).
Learning to operate <system> was easy for me (much worse than expected … much better than expected).
Interacting with <system> did not require a lot of my mental effort (much worse than expected … much better than expected).

Appendix C

Model Specifications Using Difference Scores and Direct Measures

Much prior expectation disconfirmation research has either used difference scores or direct measurement models to examine the relationship among expectations, experiences, and outcome variables. Below, we briefly explain these models and present the results of these models using our empirical data.

Table C1. Summary of Model Tests

Theoretical Model	Tests	Model Tests
Assimilation	Algebraic difference Direct Measurement	$Z = b_0 + b_1 (X – Y)$ $Z = b_0 + b_1 (D)$
Contrast	Algebraic difference Direct Measurement	$Z = b_0 + b_1 (X – Y)$ $Z = b_0 + b_1 (D)$
Generalized Negativity	Squared difference Squared Direct Measurement	$Z = b_0 + b_1 (X – Y)^2$ $Z = b_0 + b_1 (D)^2$
Assimilation-Contrast	Cubic difference Cubic Direct Measurement	$Z = b_0 + b_1 (X – Y)^3$ $Z = b_0 + b_1 (D)^3$

Note: D = direct measure of disconfirmation; Z = outcome; X = experience; Y = expectation; b1 = coefficient of the difference score or the direct measure of the difference score.

Difference Score Models

Based on the nature of the relationship (linear or curvilinear), Edwards and Harrison (1993) and Edwards (2002) describe the use of two types of difference score models: (1) algebraic difference where $Z = b_0 + b_1 (X - Y) + e$, and (2) squared difference: $Z = b_0 + b_1 (X - Y)^2$. Edwards also presents an absolute difference model where $Z = b_0 + b_1 (1 - 2W)(X - Y) + e$ with $W = 0$ when $X > Y$ and $W = 1$ when $X < Y$ or $Z = b_0 + b_1X - b_1Y - 2b_1WX + 2b_1WY + e$, but this model is rarely used. Edwards argues that these difference score models distort the true relationship between component measures (i.e., X and Y) that may result in oversimplified or erroneous results (for a review, see Edwards 2002).

Direct Measurement Models

In order to avoid the problems with difference scores, Irving and Meyer (1994, 1995, 1999) discussed prior research that used direct measurement models, where the difference between X and Y (component measures) was directly measured instead of being computed. Irving and Meyer (1994, 1995, 1999) illustrate that direct measurement models not only suffer from problems associated with difference scores, but also create additional problems (see Venkatesh and Goyal 2010).

Model Testing: Linear Models

Because the assimilation model and the contrast model are both linear models represented by the equation $Z = b_0 + b_1U_1 + b_2U_2 + e$, their constrained models can also be represented by an algebraic difference model and a linear direct measurement model. Recall that the assimilation model requires expectations to be a dominant predictor of the outcome whereas the contrast model requires experiences to be a dominant predictor of the outcome. Therefore, we expect the coefficient of the difference score (experiences – expectations) and the direct measure to be negative for the assimilation model and positive for the contrast model.

The results of the constrained difference scores model for all three dependent variables (i.e., BI, use, and satisfaction) are presented in Tables C2–C4. The results of the constrained direct measurement model for all three dependent variables (i.e., BI, use, and satisfaction) are presented in Table C5. The coefficient of the difference score (BI: 0.30, $p < .01$; use: 0.24, $p < .01$; and satisfaction: 0.24, $p < .001$) is positive for all three dependent variables, indicating that the assimilation model is not supported by the difference score model. The coefficient of the direct measure (BI: 0.24, $p < .001$; use: 0.23, $p < .001$; and satisfaction: 0.23, $p < .001$) is also positive for all three dependent variables indicating that the assimilation model is not supported by the direct measurement model. Edwards (2002) explains that for a constrained model to support a theoretical model, an unconstrained model should not explain higher variance in the outcome variable than the constrained model. Because the variance explained by the constrained models (i.e., difference scores and direct measurement models) is significantly less than the variance explained by an unconstrained linear model (see Tables 4–6), both assimilation and contrast models are rejected. Moreover, significantly higher variance explained by the curvilinear difference scores and direct measurement models (see Tables C2–C5) provides further evidence that both assimilation and contrast models are rejected.

Model Testing: Curvilinear Models

As the generalized negativity model involves a second-order curvilinear relationship and is represented by the equation $Z = b_0 + b_1U_1 + b_2U_2 + b_3U_1^2 + b_4U_1U_2 + b_5U_2^2 + e$, this model can be tested by the squared difference model and the direct measurement model where a square of the direct measurement term would be used. Recall that the generalized negativity model requires that the outcome variable is maximized when expectations are equal to experiences. As differences between expectations and experiences increase, the outcome variable decreases. Therefore, we expect the coefficient of the squared difference score term and the squared difference score term to be negative and significant. As presented in Tables C2–C4, the coefficient of the difference score (BI: 0.07, n.s.; use: 0.16, $p < .05$; and satisfaction: 0.13, $p < .05$) and the direct measure (BI: 0.23, $p < .001$; use: 0.13, $p < .05$; and satisfaction: 0.14, $p < .05$) were positive for all three dependent variables indicating that the generalized negativity model is not supported. Moreover, the unconstrained model explained more variance ($R^2 = 0.58$ for BI; $R^2 = 0.51$ for Use; $R^2 = 0.53$ for Sat) than the constrained model, providing further evidence that the generalized negativity model is not supported.

Finally, the assimilation-contrast model involves a third-order curvilinear relationship because of two inflection points and is represented by $Z = b_0 + b_1U_1 + b_2U_2 + b_3U_1^2 + b_4U_1U_2 + b_5U_2^2 + b_6U_1^3 + b_7U_1^2 U_2 + b_8U_1U_2^2 + b_9U_2^3 + e$. This model can be tested by a cubic difference model and the direct measurement model where a cubic term of the direct measurement term would be used. This model is not tested by Edwards

(2002) but would follow the same line of reasoning as the squared difference model and will be represented by $Z = b_0 + b_1 (X - Y)^3$. Recall that for the assimilation-contrast model, outcome is explained by expectations for small differences in expectations and experiences and outcome is explained by experiences for large differences in expectations and experiences. Such a relationship is represented by a wave-shaped graph along the X-Y axis which requires the coefficient of $(U_1 - U_2)^3$ and their direct measure to be significant. As presented in Tables C2–C4, the coefficient of the difference score (BI: 0.08, n.s.; use: 0.12, $p < .05$; and satisfaction: 0.07, n.s.) and the direct measure (BI: 0.13, $p < .05$; use: 0.13, $p < .05$; and satisfaction: 0.16, $p < .05$) were either not significant or marginally significant. Moreover, the unconstrained model explained more variance ($R^2 = 0.69$ for BI; $R^2 = 0.70$ for Use; $R^2 = 0.68$ for Sat) than the constrained model, providing further evidence that the assimilation-contrast model is not supported.

Table C2. Constrained Model: Predicting BI_2 Using Difference Scores

	Difference Scores Model			Squared Difference Scores Model			Cubic Difference Scores Model		
Independent Variable	R^2	B	SE	R^2	B	SE	R^2	B	SE
Age	0.35	-0.12*	0.01	0.37	-0.12*	0.01	0.38	-.10	.02
Gender		0.21**	0.02		0.21**	0.02		0.20**	0.02
EOU_1		0.08	0.03		0.08	0.03		0.07	0.04
EOU_2		0.20**	0.01		0.22**	0.02		0.21**	0.02
BI_1		0.46***	0.03		0.44***	0.02		0.43***	0.02
$(U_1 - U_2)$		0.30***	0.07		0.24***	0.08		0.21**	0.07
$(U_1 - U_2)^2$					0.07	0.05		0.04	0.05
$(U_1 - U_2)^3$								0.08	0.03
ΔR^2				0.02*			0.01		

Notes:
1. BI_2 = behavioral intention measured at t_2; BI_1 = behavioral intention measured at t_1; EOU_1 = experienced ease of use; EOU_2 = expected ease of use; U_1 = experienced usefulness; U_2 = expected usefulness.
2. Control variables: EOU_1, EOU_2, Gender (1 represents women), and Age.
3. Variables measured at time t_1: EOU_2, U_2, BI_1, Gender, and Age.
4. Variables measured at time t_2: EOU_1, U_1, BI_2.
5. *$p < .05$; **$p < .01$; ***$p < .001$.

Table C3. Constrained Model: Predicting Use_{23} Using Difference Scores

	Difference Scores Model			Squared Difference Scores Model			Cubic Difference Scores Model		
Independent Variable	R^2	B	SE	R^2	B	SE	R^2	B	SE
Age	0.37	-0.07	0.02	0.40	-0.05	0.02	0.42	-0.04	0.01
Gender		0.23**	0.02		0.21**	0.02		0.20**	0.02
EOU_1		0.07	0.03		0.06	0.03		0.04	0.04
EOU_2		0.22**	0.03		0.21**	0.02		0.20**	0.02
Use_{12}		0.43***	0.06		0.40***	0.06		0.35***	0.06
$(U_1 - U_2)$		0.24**	0.06		0.20*	0.08		0.17*	0.08
$(U_1 - U_2)^2$					0.16*	0.03		0.14*	0.03
$(U_1 - U_2)^3$								0.12*	0.02
ΔR^2				0.03*			0.02*		

Notes:
1. Use_{12} = use measured from t_1 to t_2; Use_{23} = use measured from t_2 to t_3; EOU_1 = experienced ease of use; EOU_2 = expected ease of use; U_1 = experienced usefulness; U_2 = expected usefulness.
2. Control variables: EOU_1, EOU_2, Gender (1 represents women), and Age.
3. Variables measured at time t_1: EOU_2, U_2, Use_{12}, Gender, and Age.
4. Variables measured at time t_2: EOU_1, U_1, Use_{23}.
5. *$p < .05$; **$p < .01$; ***$p < .001$.

Table C4. Constrained Model: Predicting Sat_2 Using Difference Scores

	Difference Scores Model			Squared Difference Scores Model			Cubic Difference Scores Model		
Independent Variable	**R^2**	**B**	**SE**	**R^2**	**B**	**SE**	**R^2**	**B**	**SE**
Age	0.35	-0.13*	0.01	0.41	-0.12*	0.01	0.42	-0.12*	0.01
Gender		0.24*	0.05		0.20*	0.06		0.17*	0.07
EOU_1		0.06	0.05		0.04	0.05		0.03	0.06
EOU_2		0.33***	0.01		0.30***	0.01		0.28***	0.02
Sat_1		0.80***	0.06		0.76***	0.06		0.73***	0.05
$(U_1 - U_2)$		0.24***	0.03		0.20*	0.07		0.17*	0.07
$(U_1 - U_2)^2$					0.13*	0.02		0.12*	0.02
$(U_1 - U_2)^3$								0.07	0.02
ΔR^2				0.06***			0.01		

Notes:

1. Sat_2 = satisfaction measured at t_2; Sat_1 = satisfaction measured at t_1; EOU_1 = experienced ease of use; EOU_2 = expected ease of use; U_1 = experienced usefulness; U_2 = expected usefulness.
2. Control variables: EOU_1, EOU_2, Gender (1 represents women), and Age.
3. Variables measured at time t_1: EOU_2, U_2, Sat_1, Gender, and Age.
4. Variables measured at time t_2: EOU_1, U_1, Sat_2.
5. *p < .05; **p < .01; ***p < .001.

Table C5: Constrained Model: Predicting BI_2, Use_{23}, Sat_2 Using Direct Measures

		Direct Measurement Model			Squared Direct Measurement Model			Cubic Direct Measurement Model		
Dependent Variable	**Independent Variables**	**R^2**	**B**	**SE**	**R^2**	**B**	**SE**	**R^2**	**B**	**SE**
BI_2	Age	0.33	-0.15*	0.02	0.41	-0.12*	0.02	0.46	-0.07	0.04
	Gender		0.25***	0.02		0.21***	0.02		0.15*	0.03
	DEOU		-0.21***	0.03		-0.17*	0.03		-0.14*	0.03
	BI_1		0.46***	0.02		0.38***	0.02		0.35***	0.02
	DU		0.24***	0.02		0.21***	0.02		0.17*	0.03
	DU^2					0.23***	0.03		0.20**	0.03
	DU^3								0.13*	0.02
	ΔR^2				0.08***			0.05**		
Use_{23}	Age	0.31	-0.07	0.02	0.35	-0.05	0.03	0.38	-0.04	0.03
	Gender		0.22**	0.02		0.20**	0.03		0.17*	0.03
	DEOU		-0.13*	0.02		-0.12*	0.02		-0.12*	0.03
	Use_{12}		0.42***	0.03		0.40***	0.03		0.35***	0.03
	DU		0.23***	0.02		0.20***	0.02		0.17**	0.02
	DU^2					0.13*	0.04		0.12*	0.04
	DU^3								0.13*	0.03
	ΔR^2				0.04*			0.03*		
Sat_2	Age	0.33	-0.13*	0.01	0.37	-0.12*	0.02	0.41	-.0.10	0.03
	Gender		0.23**	0.02		0.21**	0.02		0.17**	0.03
	DEOU		0.22**	0.04		0.20**	0.04		0.17**	0.04
	Sat_1		0.77***	0.04		0.70***	0.05		0.66***	0.05
	DU		0.23***	0.02		0.21***	0.03		0.19**	0.03
	DU^2					0.14*	0.04		0.10	0.05
	DU^3								0.16*	0.02
	ΔR^2				.04*			0.04*		

Notes:

1. DU = disconfirmation of usefulness; DEOU = disconfirmation of ease of use; BI_1 = behavioral intention measured at t_1; BI_2 = behavioral intention measured at t_2; Sat_1 = satisfaction measured at t_1; Sat_2 = satisfaction measured at t_2; Use_{12} = use measured from t_1 to t_2; Use_{23} = use measured from t_2 to t_3.
2. Control variables: DEOU, Gender (1 represents women), and Age.
3. Variables measured at time t_1: DEOU, DU, BI_1, Use_{12}, Sat_1, Gender, and Age.
4. Variables measured at time t_2: BI_2, Use_{23}, Sat_2.
5. *p<.05; **p<.01; ***p<.001.

References

Edwards, J. R. 2002. "Alternatives to Difference Scores: Polynomial Regression Analysis and Response Surface Methodology," in *Measuring and Analyzing Behavior in Organizations: Advances in Measurement and Data Analysis,* F. Drasgow and N. Schmidt (eds.), San Francisco: Jossey-Bass/Pfeiffer, pp. 350-400.

Edwards, J. R., and Harrison, R. V. 1993. "Job Demands and Worker Health: Three-Dimensional Reexamination of the Relationship between Person–Environment Fit and Strain," *Journal of Applied Psychology* (78:4), pp. 628-648.

Irving, P. G., and Meyer, J. P. 1995. "On Using Direct Measures of Met Expectations: A Methodological Note," *Journal of Management* (21:6), pp. 1159-1175.

Irving, P. G., and Meyer, J. P. 1999. "On Using Residual Difference Scores in the Measurement of Congruence: The Case of Met Expectations Research," *Personnel Psychology* (52:1), pp. 85-86.

Venkatesh, V., and Goyal, S. 2010. "Expectation Disconfirmation and Technology Adoption: Polynomial Modeling and Response Surface Analysis," *MIS Quarterly* (34:2), pp. 281-303.

Appendix D

Slopes along Lines of Interest[1]

A **linear equation** can be presented by

$Z = b_0 + b_1X + b_2Y + e$

Slopes along lines of interest for such a linear equation are given by:

Confirmation axis (X = Y line):

Linear slope (a_x) is given by: $b_1 + b_2$

Disconfirmation axis (X = -Y line):

Linear slope (a_y) is given by: $b_1 - b_2$

A **quadratic equation** can be presented by:

$Z = b_0 + b_1X + b_2Y + b_3X^2 + b_4XY + b_5Y^2 + e$

Slopes along lines of interest for such a quadratic equation are given by:

Confirmation axis (X = Y line):

Linear slope (a_x) is given by: $b_1 + b_2$

Quadratic slope (a_x^2) is given by: $b_3 + b_4 + b_5$

Disconfirmation axis (X = -Y line):

Linear slope (a_y) is given by: $b_1 - b_2$

Quadratic slope (a_y^2) is given by: $b_3 - b_4 + b_5$

A **cubic equation** can be presented by:

$Z = b_0 + b_1X + b_2Y + b_3X^2 + b_4XY + b_5Y^2 + b_6X^3 + b_7X^2Y + b_8XY^2 + b_9Y^3 + e$

Slopes along lines of interest for such a cubic equation are given by:

Confirmation axis (X = Y line):

Linear slope (a_x) is given by: $b_1 + b_2$

Quadratic slope (a_x^2) is given by: $b_3 + b_4 + b_5$

Cubic slope (a_x^3) is given by: $b_6 + b_7 + b_8 + b_9$

Disconfirmation axis (X = -Y line):

Linear slope (a_y) is given by: $b_1 - b_2$

Quadratic slope (a_y^2) is given by: $b_3 - b_4 + b_5$

Cubic slope (a_y^3) is given by: $b_6 - b_7 + b_8 - b_9$

[1]See Brown et al. (2012), Edwards (2002), and Edwards and Parry (1983).

References

Brown, S. A., Venkatesh, V., and Goyal. S. 2012. "Expectation Confirmation in Technology Use," *Information Systems Research* (23:2), pp. 474-487.

Edwards, J. R. 2002. "Alternatives to Difference Scores: Polynomial Regression Analysis and Response Surface Methodology," in *Measuring and Analyzing Behavior in Organizations: Advances in Measurement and Data Analysis,* F. Drasgow and N. Schmidt (eds.), San Francisco: Jossey-Bass/Pfeiffer, pp. 350-400.

Edwards, J. R., and Parry, M. E. 1993. "On the Use of Polynomial Regression Equations as an Alternative to Difference Scores in Organizational Research," *Academy of Management Journal* (36:6), pp. 1577-1613.