Examining the "Urban Legend" of Common Method Bias: Nine Common Errors and their Impact

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Abstract

In this paper, we examine the "urban legend" of CMB and question the impact of nine common errors that researchers make when designing survey instrument. We define the nine most common errors and implement these errors in an empirical study of 537 undergraduate students enrolled in an Introductory Psychology course at a large southeastern university. By analyzing this data in PLS, we discover that each of the sources of CMB differently impacts the measurement and structural model for researchers.

1. Introduction

Common method bias (also known as common method variance or monomethod bias) represents one of the most frequently cited concerns among IS researchers (Straub et al, 2004; Malhotra et al, 2006) and social scientists (Campbell and Fiske, 1959; Feldman and Lynch 1988; Podsakoff et al, 2003). Common Method Bias (or CMB) occurs when the same method is used to measure correlations between variables. In a standard survey study, an individual subject responds to the items in a particular survey at one point in time. In these instances, the data is susceptible to CMB (Kemery and Dunlap 1986, Lindell and Whitney 2001). Since self-report surveys are the most frequently utilized method of data collection in the information systems field (Hufnagel and Conca, 1994), this issue denotes an important topic for the research community.

Although many researchers are aware of the potential problems of CMB arising from the use of a single-method study, disunity about the actual affect of CMB is widespread (Crampton and Wagner, 1994; Lindell and Whitney, 2001). While some argue that CMB accounts for one of the primary sources of measurement error (Podsakoff et al, 2003), others believe that CMB is an urban legend, and that the impact has been over-rated (Spector, 2006). It is the objective of our study to examine the "urban legend" of CMB to determine the source and the impact.

2. Sources of Common Method Bias

A recent review of CMB revealed sixteen causes of bias (Podsakoff et al. 2003). As an initial, exploratory study, we chose to focus on nine of those sixteen sources. We are not arguing that this is a comprehensive study. Rather, we are focusing on what we view are the nine most common errors made by IS researchers in order to understand how these nine errors influence our research results.

2.1. Source 1: Ambiguous or complex items

One source of CMB is to author items that are either ambiguously worded or that are complex (e.g. containing a joint item that contains two phrases). This is a source of CMB, as ambiguous or complex items tend to impose on the respondent the need to develop its own idiosyncratic meaning and thus may increase the level of random error as well as systematic measurement error. As a result, we would expect complex items in constructs to have lower internal consistency, thus reducing construct reliability.

2.2. Source 2: Format of the scales and choice of scale anchors

The second source of CMB is to rely upon a single format for either the scale or scale anchors. This contributes to CMB, as, depending on the scales used, the general response set may be systematically biased upwards or downwards depending on how the scale is formatted. The impact of not altering the scales is that latent variable scores containing items affected by this type of bias are systematically upwards or downwards biased.

2.3. Source 3: Negatively worded or reverse coded items

The third source of CMB is to include negatively worded or reverse coded items within positively worded items. Reverse-coded items may not be recognized by respondents and tend to be answered in a different manner compared to their normal counterparts, indicating systematic bias. As a result, we would expect reverse-coded items to not load heavily on a construct, thus also reducing construct reliability.

2.4. Source 4: Item priming effects

The fourth source of CMB is the inclusion of an introduction that informs the respondent about what the items are attempting to measure before the respondent views the items, thereby increasing the face validity of the items. The effect of this source is the production a systematic, upward bias on the following items. If items of different constructs are affected, this will likely reduce construct reliability, if items from the same construct are affected, this construct will create artificially high internal consistency and scale reliability.

2.5. Source 5: Item embeddedness

The fifth source of CMB is including neutrally valenced items within either positive or negatively worded items. As a result of including these types of items, the neutral items take over the positive or negative meaning of adjacent items. Similar to negatively worded or reverse coded items, we would expect reverse-coded items to not load correctly on a construct, thus also reducing construct reliability.

2.6. Source 6: Consistency motif or consistency effect

The sixth source of CMB is that people try to maintain consistency between their cognitions and attitudes. As a result, it is likely that people answering to questions by a researcher would try to appear consistent and rational in their responses, thereby imposing a bias on relationships that otherwise would eventually not exist. The impact of this source is that path coefficients might show relations that might not exist, or that path coefficients are biased upwards.

2.7. Source 7: Social desirability

The seventh source of CMB is that respondents try to answer to specific questions (e.g. regarding their age or profession) to represent themselves in a more favorable light. Specifically, this is likely to be true for questions that are emotionally sensitive or imbued with a stigma. The impact of this bias is that the latent value scores of constructs containing questions vulnerable to social desirability are upward biased.

2.8. Source 8: Positive and negative affectivity

The eighth source of CMB is that depending on their mood state, respondents will follow a response state consistent with their mood, rating all items in a questionnaire more negatively or positively (See Jackson, 1967; Rorer, 1965 for more information). If only some people are affected, the total effects should not influence the results, however, if all respondents are systematically positively or negatively affected in the same way, there will be systematic effects in the data. We would expect that the impact of the mood of the respondent to inflate (or deflate) item and path scores.

2.9. Source 9: Transient mood state

The ninth source of CMB is that external events or factors might influence the general mood someone is in and hence have an impact on the responses given. While the eighth source is temporal (i.e. the mood at the time that the respondent fills out the survey), the ninth source is that a series of external events that have occurred over a certain period of time (e.g. the death of a spouse or bankruptcy) will create a transient mood state in the respondent. If all respondents are consistently positively or negatively affected, these will upward or downward bias all latent variable scores.

3. Examining the Impact

3.1. Methodology

After identifying the nine most common sources of CMB, we next step needed a research model and context to examine how these nine sources materialize. Rather than relying upon Monte Carlo data, we were interested in a real-life study to examine how these sources impact actual research results. As researchers that focus on IT adoption research issues, we decided to contextualize our study within this research domain.

Based upon prior work that has found that individual characteristics influence beliefs about technology (e.g. Agarwal and Prasad, 1998; Lewis, et al, 2003), our research model hypothesized that Personal Innovativeness in the domain of information technology (PIIT) and computer self-efficacy (CSE) has a positive (and significant) influence on beliefs about technology (specifically the ease of use and relative advantage of the technology) and that ease of use influences relative advantage. Theoretically, we are suggesting that individual differences influence technology perceptions and that the easier the technology is perceived to be, the more an individual will see advantages in using the technology. We have depicted our research model below in Figure 1.

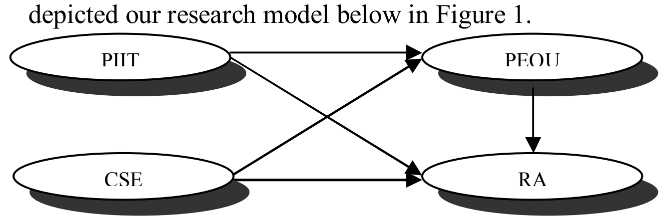

Figure 1 Research Model

3.2. Research Design

To understand the impact of the nine sources of CMB, we first divided the nine sources into two categories: (1) Sources that could be manipulated versus (2) Sources that could not be manipulated. Our research approach was to include one version of the questionnaire with no manipulation (the baseline questionnaire) and that all of the nine sources of CMB would be compared against the CMB. Respondents were first randomly assigned into one of two versions of the questionnaire – version A was not manipulated and version B was the five manipulated versions (see Figure 2 below). Subjects assigned in to Version B were then randomly assigned in to one of the five manipulated questionnaire adaptations. Overall, 30% of respondents were assigned into the baseline questionnaire, and 14% were assigned into each of the manipulated versions (B1 to B5). Our design called for us to sub-divide the respondents within Version A to examine the impact of the four non-manipulated sources, assuming no randomization of the constructs or the items. We will expand upon this after discussing construct operationalization.

3.3. Subjects

Questionnaire data were collected from 537 undergraduate students enrolled in an Introductory Psychology course at a large southeastern university. Participation in the study was voluntary, compensated with in-class extra credit, and yielded an overall response rate of 83%, with rates per condition ranging from 59% (B1) to 92% (B5). The average participant was 19 years of age (standard deviation = 1.19), 70% of whom were in their second year in college (18% in their third year), with 9% majoring in psychology. Half were experienced using the Blackboard course management system with 12 months of experience or more.

Table 1 Profile of Assignments

Questionnaire Version	Number of Subjects
Baseline	172
B_1	53
B_2	77
B_3	77
B_4	75
B_5	83
Total	537

3.4. Operationalization of the Constructs

The constructs in the research model were operationalized through items validated in prior research studies. We decided to leave three of the four constructs constant, only altering one construct for our design. Given our objective to understand sources of CMB such as social desirability, we needed to select a construct that would be upwardly biased – we chose PIIT as the construct that we would manipulate for our study.

3.4.1. Personal Innovativeness in the domain of information technology. Personal Innovativeness in the domain of information technology is defined as the willingness of an individual to try out any new innovation (Agarwal and Prasad, 1998). Items were adapted from Agarwal and Prasad (1998) and are included in Appendix A. In the original scale, PIIT3 was negatively worded ("In general, I am eager to try out new information technologies."), however, for the baseline survey, this wording was altered so that all four items were positively valenced. For the manipulated sources of CMB, two items were changed (PIIT2 and PIIT4) to examine the impact.

3.4.2. Computer Self Efficacy. Computer self-efficacy is defined as an individual's judgment of one's capability to use a computer (Compeau and Higgins, 1995). Items were written specifically for this study to assess students' comfort and efficacy using the Blackboard system adopted in this classroom context. The items are in Appendix B.

3.4.3. Ease of Use. Ease of use is defined as the degree to which an individual believes that using a particular system would be free of physical and mental effort (Moore and Benbasat, 1991). Items were taken from Moore and Benbasat (1991) and were adapted for our research context. The items are included in Appendix B.

3.4.4. Relative Advantage. Relative advantage is defined as the degree to which an innovation is perceived as being better than its precursor (Moore and Benbasat, 1991). Items were taken from Moore and Benbasat (1991) and were adapted for our research context. The items are in Appendix B.

3.5. Measuring Un-manipulated Sources of CMB

While the subjects were randomly assigned in to the treatment groups, the impact of the un-manipulated sources of CMB was operationalized by splitting up the baseline population into two groups.

3.5.1. Measuring the Consistency Motif. As part of our survey instrument, we asked each respondent to identify other students that they knew in the class. The subject then had to identify how frequently that he/she had contact with the other student and whether or not he/she intended to keep in contact with that other student after the class ended. After assessing their own individual perception towards Blackboard, the subject was then asked about that other individual's perceived innovativeness (The items are included in Appendix C). We would expect that the rating of a friend does not incorporate a consistency effect, as the individual is not attempting to maintain a consistency in perceptions. Thus, if self-report and friend-report are dramatically different, this is an indication for a consistency effect. All 172 students in the baseline group were included in this analysis.

3.5.2. Measuring Social Desirability. While the consistency motif examined if there was a difference between how the subject assessed themselves versus the rating of the other, social desirability was assessed by examining how someone else assessed the subject (The items are included in Appendix C). If we assume that the rate-a-friend ratings are objective, we could interpret deviations as related to such problematic questions as induced by social desirability. Each student could, on an open-ended basis, answer the PIIT questions about another student, thus, we needed a matched set. When locating matched sets, 48 students were included.

3.5.3. Measuring Positive and negative affectivity. To assess the mood of the student at the time while completing the survey, the respondent filled out the 20-item Positive and Negative Affect Schedule (or PANAS, from Watson, et al., 1988). These 20 items are half positive affects and half negative affects. For each respondent, the positive items were summed and the average for the entire baseline set was computed. Those subjects whose sum was above the average were categorized as "More Positive," while those that were below the average were categorized as "Less Positive." According to this operational definition, 91 subjects were more positive and 81 were less positive.

3.5.4. Measuring Transient mood state. To examine if the transient mood state influenced the respondent, each subject filled out the Major Life Events for Students scale. Each student was asked if a set of events had occurred to them over the past year (from Clements and Turpin, 1996). If the student experienced the event, they were assigned a score corresponding to that particular circumstance (the weighting is in parenthesis). The higher the score, the more major life events that occurred to the student, while the lower, the less major life events. The average life events score for the entire baseline set was computed and those subjects whose sums were above the average were categorized as "High amount of external events" and those below the average were termed "Low amount of external events." 80 students had a high score and 92 low.

3.6. Data Analysis and Results

PLS, a latent structural equations modeling technique, was utilized to test the differences between the sources of CMB. PLS uses a component-based approach to estimation that places minimal demands on sample size and the normality of data distributions (Chin, 1998). Given the small sample size within each of the sources, PLS was appropriate for our data analysis. We analyzed both the structural and measurement model for all nine sources of CMB, as compared to the baseline.

3.6. Measurement Model

The first step in a PLS analysis is the analysis of the measurement (or outer) model. First, we examined the adequacy of the measures to ensure that the items measured the constructs as they were designed. Chin (1998) prescribes a guideline for the adequacy of the items: "Standardized loadings should be greater than 0.707....But it should also be noted that this rule of thumb should not be as rigid at early stages of scale development. Loadings of 0.5 or 0.6 may still be acceptable if there are additional indicators in the block for comparison basis" (p. 325). Tables 2a and 2b includes all of the loadings.

The results demonstrate that ambiguous or complex items and item priming lead to higher loadings and that the format of the scales, negatively worded, and item embeddedness lead to lower loadings. We also found that a more positive outlook contributes to higher loadings and that stressful events lead to inflated scores. We found no evidence of the consistency effect or social desirability.

Second, to determine whether the items loaded on other constructs, as well as on their theorized construct, we computed cross-loadings (not included due to space limitations). For cross-validated items to be included in the finalized data set, the loading must be larger on the intended construct than on any other constructs. Consequently, on determining that none of the items loaded higher on any construct other than the intended construct, we included all the items.

Third, using the loadings from the constructs in the model, we created composite reliabilities for the variables in the model. The table below shows the composite reliabilities for each construct. The results indicate that all the variables met the recommended value of 0.80 and thus are reliable.

Table 2a Item Loadings for Manipulated Sources

	Baseline			Ambiguous Question			Item Embededness			Item Priming			Negative Wording			Scale Format		
	Weight	Loading	T-statistic	Weight	Loading	T-statistic	Weight	Loading	T-statistic	Weight	Loading	T-statistic	Weight	Loading	T-statistic	Weight	Loading	T-statistic
PIIT																		
PIIT1	0.3269	0.8786	3.7382	0.2661	0.8813	3.1932	0.427	0.8619	2.9692	0.3331	0.9234	7.0776	0.3449	0.7852	4.1041	0.4098	0.7844	1.6652
PIIT2	0.2577	0.8507	2.5287	0.343	0.8825	4.597	0.2612	0.6673	1.6957	0.2882	0.9036	6.9686	-0.217	-0.6505	2.9339	0.2747	0.7463	1.7667
PIIT3	0.3739	0.9135	3.6993	0.2511	0.9191	3.6811	0.2121	0.8664	1.6257	0.2257	0.9419	4.3034	0.3658	0.8064	4.462	0.3021	0.8592	2.6243
PIIT4	0.1788	0.8498	1.5058	0.2713	0.8548	5.2918	0.2983	0.9181	3.1815	0.2323	0.9445	7.3225	-0.3721	-0.7877	4.9216	0.2704	0.7915	1.5984
PEOU																		
EOU1	0.2854	0.9144	20.104	0.3324	0.8789	5.7093	0.2585	0.879	9.9177	0.3089	0.8851	9.4974	0.3042	0.918	15.4509	0.2851	0.9153	15.4203
EOU2	0.2674	0.8494	17.9704	0.208	0.7207	1.7925	0.321	0.8669	9.6305	0.303	0.9184	19.704	0.254	0.8811	17.503	0.2728	0.9087	14.4887
EOU3	0.2793	0.9138	20.805	0.2962	0.7958	5.2015	0.2893	0.8992	17.1695	0.2678	0.8977	13.8096	0.2973	0.918	18.3187	0.279	0.9048	24.71
EOU4	0.2841	0.9034	19.6	0.3519	0.9156	6.2808	0.2782	0.8425	12.5031	0.2394	0.8683	11.2251	0.2551	0.8783	17.9942	0.259	0.9218	25.2381
RA																		
RA1	0.2765	0.8536	14.8165	0.3013	0.9046	3.7105	0.2745	0.9197	19.92	0.2745	0.9442	21.1888	0.3026	0.874	10.862	0.2634	0.929	15.8072
RA2	0.307	0.9131	13.4798	0.2865	0.9672	9.8046	0.262	0.9128	19.142	0.2782	0.9417	18.1148	0.3065	0.9483	12.779	0.2721	0.9411	17.5861
RA3	0.2359	0.926	16.645	0.2537	0.9427	6.7958	0.2671	0.9527	20.4096	0.2412	0.9184	13.0992	0.227	0.8007	5.7647	0.2671	0.9234	16.2137
RA4	0.2984	0.8887	16.3862	0.2392	0.8828	4.1056	0.2737	0.9277	16.7466	0.2801	0.9182	15.4355	0.288	0.9136	13.6234	0.277	0.912	11.9667
SE																		
SE1	0.5927	0.9429	10.5413	0.5152	0.9739	17.7097	0.5378	0.9315	10.7622	0.4955	0.9772	41.8964	0.544	0.9536	19.774	0.5259	0.9803	28.0939
SE2	0.4833	0.9128	16.3827	0.5118	0.9736	18.506	0.536	0.931	11.7534	0.5264	0.9798	53.7203	0.5084	0.9467	30.4175	0.4955	0.9778	42.5824

Table 2b Item Loadings for un-manipulated sources of CMB

	More Positive			Less Positive			High Amount of Events			Low Amount of Events			Consistency			Social Desirability		
	Weight	Loading	T-statistic	Weight	Loading	T-statistic	Weight	Loading	T-statistic	Weight	Loading	T-statistic	Weight	Loading	T-statistic	Weight	Loading	T-statistic
PIIT																		
PIIT1	0.3765	0.8899	4.6104	0.0453	0.7768	0.1297	0.3461	0.8729	3.9926	0.236	0.8473	1.0118	0.2436	0.9741	17.9354	0.0909	0.3381	0.2709
PIIT2	0.2674	0.8277	2.5932	0.2352	0.8468	1.0013	0.2093	0.8389	1.8639	0.4394	0.9056	1.5339	0.2564	0.9762	21.5877	0.626	0.9811	2.1207
PIIT3	0.359	0.8913	4.5275	0.4611	0.9477	1.995	0.3315	0.9184	4.2805	0.4512	0.9084	1.1935	0.275	0.9712	15.9941	0.3136	0.9253	2.5896
PIIT4	0.1479	0.8361	1.0861	0.3642	0.9023	1.9773	0.2435	0.895	2.7996	-0.0106	0.7289	0.0288	0.2521	0.9729	20.8529	0.0817	0.7947	0.2791
PEOU																		
EOU1	0.2972	0.9143	13.9158	0.269	0.9165	25.7705	0.2726	0.9393	20.9306	0.3008	0.8841	11.8082	0.3039	0.885	10.8876	0.2877	0.9042	11.7756
EOU2	0.2613	0.7849	10.9166	0.2771	0.9314	19.9909	0.2686	0.8879	17.1552	0.2693	0.8122	10.4402	0.2695	0.8124	10.7626	0.2333	0.8334	11.4528
EOU3	0.2793	0.8906	14.1037	0.2794	0.9506	22.0667	0.2682	0.9642	25.1234	0.2904	0.8599	11.939	0.2894	0.8595	11.521	0.3021	0.9558	12.0757
EOU4	0.2974	0.9227	14.1483	0.2624	0.8754	19.1167	0.2675	0.9228	23.1029	0.3019	0.8796	11.0289	0.2996	0.8789	11.3235	0.2833	0.906	13.3695
RA																		
RA1	0.2978	0.8752	11.6335	0.2522	0.8246	7.577	0.2908	0.8431	6.4071	0.2706	0.8617	11.9951	0.2623	0.8592	12.5053	0.2952	0.9087	14.4137
RA2	0.2888	0.9228	11.5043	0.3367	0.8972	9.0942	0.2921	0.9213	5.915	0.3127	0.91	12.8883	0.3081	0.9093	13.9878	0.2836	0.947	13.8131
RA3	0.2299	0.942	11.9591	0.2445	0.9028	7.955	0.2218	0.9243	7.0586	0.2547	0.9293	12.8537	0.2594	0.9304	16.0145	0.2254	0.9278	10.8512
RA4	0.2821	0.9085	13.8781	0.3155	0.8532	7.7723	0.3219	0.8721	8.8823	0.2736	0.8977	13.1012	0.2813	0.8999	13.8554	0.285	0.8914	13.1478
SE																		
SE1	0.5055	0.9754	76.739	0.686	0.9352	6.4306	0.6352	0.9404	7.3317	0.5251	0.9589	40.2368	0.525	0.9589	36.531	0.6707	0.9441	6.4488
SE2	0.519	0.9767	58.0146	0.433	0.8279	5.4461	0.4569	0.8812	8.95	0.5183	0.9578	41.5187	0.5185	0.9578	45.1417	0.4283	0.8564	6.248

The results demonstrate that ambiguous items and item priming resulted in higher composite reliabilities and that the format of the scale, negatively worded items, and item embeddedness leads to lower. There was no difference for positive and negative affectivity and consistency resulted in a higher reliability, while social desirability was lower. Table 3 includes all of the composite reliabilities.

Table 3 Composite Reliabilities

	Baseline	Ambiguous	Item Embedefdness	Item Priming	Negative Wording	Scale Format
PIIT	0.928	0.935	0.900	0.962	0.845	0.874
PEOU	0.942	0.899	0.927	0.94	0.944	0.952
RA	0.942	0.959	0.961	0.963	0.936	0.96
SE	0.925	0.973	0.929	0.978	0.949	0.979

	More Positive	Less Positive	High Event #	Low Event #	Consistency	Social Desirability
PIIT	0.920	0.926	0.933	0.912	0.986	0.865
PEOU	0.932	0.956	0.962	0.919	0.919	0.945
RA	0.952	0.926	0.939	0.945	0.945	0.956
SE	0.976	0.876	0.907	0.957	0.957	0.896

Table 4 presents the average variance extracted and the correlations between the constructs. A comparison of the square root of the average variance extracted with the correlations among constructs indicates that, on average, each construct is more highly related to its own measures than to other constructs (Chin, 1998, p. 327). Moreover, all average variances extracted were well above the 0.50 recommended level (Chin, 1998). Among the manipulated sources, item priming extracted a significant higher amount of variance than the other sources, followed by ambiguous question, item priming, scale format, and negative wording. Among unmanipulated sources, the less positive mood state extracted more than the more positive and the higher amount of external events extracted more than the lower amount. The consistency motif extracted more variance, while the social desirability was lower.

Table 4 Discriminant Validity

Baseline

	AVE	PIIT	PEOU	RA	SE
PIIT	0.763	0.873			
PEOU	0.802	0.213	0.896		
RA	0.802	0.078	0.581	0.896	
SE	0.861	0.191	0.805	0.471	0.928

Ambiguous Question

	AVE	PIIT	PEOU	RA	SE
PIIT	0.783	0.885			
PEOU	0.691	0.165	0.831		
RA	0.855	0.293	0.604	0.925	
SE	0.948	0.129	0.778	0.582	0.974

Item Embededness

	AVE	PIIT	PEOU	RA	SE
PIIT	0.695	0.834			
PEOU	0.761	0.330	0.872		
RA	0.862	0.247	0.699	0.928	
SE	0.867	0.319	0.686	0.482	0.931

Item Priming

	AVE	PIIT	PEOU	RA	SE
PIIT	0.862	0.928			
PEOU	0.797	0.340	0.893		
RA	0.866	0.313	0.596	0.931	
SE	0.957	0.373	0.685	0.455	0.978

Negative Wording

	AVE	PIIT	PEOU	RA	SE
PIIT	0.578	0.760			
PEOU	0.808	0.376	0.899		
RA	0.785	0.368	0.655	0.886	
SE	0.903	0.200	0.782	0.548	0.950

Scale Format

	AVE	PIIT	PEOU	RA	SE
PIIT	0.634	0.796			
PEOU	0.833	0.160	0.913		
RA	0.858	0.270	0.671	0.926	
SE	0.959	0.206	0.816	0.513	0.979

More Positive

	AVE	PIIT	PEOU	RA	SE
PIIT	0.743	0.862			
PEOU	0.774	0.337	0.880		
RA	0.833	0.127	0.590	0.913	
SE	0.953	0.294	0.848	0.529	0.976

Less Positive

	AVE	PIIT	PEOU	RA	SE
PIIT	0.758	0.871			
PEOU	0.844	0.077	0.919		
RA	0.757	0.056	0.584	0.870	
SE	0.780	0.040	0.785	0.417	0.883

High Amount of Events

	AVE	PIIT	PEOU	RA	SE
PIIT	0.778	0.882			
PEOU	0.863	0.307	0.929		
RA	0.794	0.116	0.584	0.891	
SE	0.830	0.255	0.816	0.519	0.911

Low Amount of Events

	AVE	PIIT	PEOU	RA	SE
PIIT	0.724	0.851			
PEOU	0.739	0.125	0.860		
RA	0.810	0.067	0.604	0.900	
SE	0.918	0.117	0.815	0.454	0.958

Consistency

	AVE	PIIT	PEOU	RA	SE
PIIT	0.948	0.974			
PEOU	0.739	0.499	0.860		
RA	0.810	0.447	0.604	0.900	
SE	0.918	0.429	0.815	0.454	0.958

Social Desirability

	AVE	PIIT	PEOU	RA	SE
PIIT	0.641	0.801			
PEOU	0.812	-0.068	0.901		
RA	0.844	-0.241	0.689	0.919	
SE	0.812	-0.040	0.842	0.537	0.901

3.7. Structural Model

Table 5 below summarizes the path loadings for each of the paths in our structural model. Beyond comparing the path loadings, we have highlighted the significant relationships, noting that the source of CMB affects both the strength and the significance of the paths for all relationships within the model.

Table 5 Path Loadings for Structural Model

	Baseline		Ambiguous		Item Embedeness		Item Priming		Negative Wording		Scale Format	
	Path	T-stat	Path	T-stat	Path	T-stat	Path	T-stat	Path	T-stat	Path	T-stat
PIIT - EOU	0.061	1.3074	0.065	0.4957	0.124	1.484	0.098	0.968	0.228	3.026	-0.008	0.1135
PIIT - RA	0.048	0.6204	0.199	1.3657	0.018	0.1962	0.116	1.1954	0.155	1.5286	0.178	1.6193
CSE - EOU	0.793	16.2232	0.77	9.2287	0.646	7.4211	0.649	5.7209	0.736	13.6758	0.818	9.6254
CSE - RA	0.011	0.0939	0.285	1.9334	0.002	0.0185	0.057	0.3399	0.129	1.0214	-0.144	0.9244
EOU-RA	0.583	5.6422	0.35	2.3115	0.691	6.7784	0.517	3.5177	0.496	3.4356	0.76	4.7902

	More Positive		Less Positive		High Amount of Events		Low Amount of Events		Consistency		Social Desirability	
	Path	T-stat	Path	T-stat	Path	T-stat	Path	T-stat	Path	T-stat	Path	T-stat
PIIT - EOU	0.096	1.2904	0.045	0.5898	0.106	1.4714	0.029	0.3361	0.182	2.2021	-0.034	0.2691
PIIT - RA	-0.082	0.7817	0.009	0.07	-0.07	0.5814	-0.007	0.0494	0.198	1.8239	-0.193	1.1572
CSE - EOU	0.82	13.3373	0.783	12.121	0.789	11.005	0.812	16.5957	0.737	12.2139	0.841	12.4876
CSE - RA	0.105	0.5636	-0.108	0.6342	0.129	0.8983	-0.114	0.6806	-0.127	0.8891	-0.139	0.5883
EOU-RA	0.528	3.0412	0.668	4.4085	0.501	3.8017	0.697	4.7228	0.608	4.4507	0.792	3.6492

4. Concluding Thoughts

The results of our empirical demonstrate the mixed influence of CMB on our research results. If we take the baseline as a reference point, we can then assess the impact of CMB on each of the elements of the measurement and structural models. In Table 6 below, we have summarized each of the sources of CMB, and the specific impacts. The far left columns summarize how the source impacts the measurement and structural model.

Taken together, our results indicate that CMB is not an "urban legend." We instead found the opposite to be true – in each case, CMB does impact our research findings – in some case, it deflates research results, while for other sources, CMB deflates our findings. While space limitations restrict our ability to expand this point, we urge our colleagues to consider the impact of our findings and to begin investigating whether our results can be replicated. If so, then the attention being given to CMB is well-deserved and should be a source of debate within our literature.

Table 6 Impact of CMB on Measurement and Structural Model

Source of CMB	Item Loadings	Composite Reliabilities	Discriminant Validity	Path Loadings	Measurement model	Structural model
Ambiguous or complex items	Slightly higher loadings	Higher	Item priming extracted a significant higher amount of variance, followed by ambiguous question, item priming, scale format, and negative wording.	Significant path not in baseline	Inflates all aspects	Inflates
Format of the scales and anchor choice	Lower loadings	Lower		Significant path not in baseline	Deflates all aspects	Inflates
Negatively worded or reverse coded	Lower loadings	Lower		Significant path not in baseline	Deflates all aspects	Inflates
Item priming effects	Higher loadings	Higher		4 of 5 paths less significant	Inflates all aspects	Deflates
Item embeddedness	Lower loadings	Lower		3 of 5 paths were less significant	Deflates all aspects	Deflates
Consistency motif or consistency effect	Compared to baseline, loadings were higher	Higher reliability	Extracted more variance	Two more significant paths	Inflates all aspects	Inflates
Social desirability	Compared to baseline, loadings were lower	Lower reliability	Extracted lower variance	3 of 5 paths were more significant	Slightly deflates all aspects	Inflates
Positive and negative affectivity	A more positive outlook contributes to higher loadings	No difference	Less positive mood extracted more than the more positive	More significant paths for more positive mood	A positive mood inflates items and deflates discriminant validity	Inflates for positive mood
Transient mood state	Stressful events lead to inflated loadings	More stress leads to higher reliabilities	Higher amount of external events extracted more than lower	More significant paths for less stressful events	Inflated for stressful events	Deflated for stressful events

5. References

Agarwal. R and I. Prasad. "A Conceptual and Optional Definition of Personal Innovativeness in the Domain of Information Technology," *Information Systems Research*, 9:2, 1998, pp. 204-215.

Campbell, D, T. and Fiske, D.. "Convergent and discriminant validation by the multitrait-multi-method matrix." *Psychological Bulletin*, 56(2), 1959, pp. 81-105.

Chin, W. W. The partial least squares approach for structural equation modeling. In G. A. Marcoulides (Ed.), *Modern methods for business research*, Mahwah, NJ: Erlbaum. 1998, pp. 295–336.

Clements, K. and Turpin, G. "The Life Events Scale For Students: Validation For Use With British Samples." *Personality and Individual Differences*, 20(6), 1996, pp. 747-751.

Compeau, D.R., and Higgins, C.A. "Computer Self-Efficacy: Development of a Measure and Initial Test." *MIS Quarterly*, 19 (2), June 1995, pp. 189-211.

Crampton, S. M. and Wagner, J. A. "Percept-percept inflation in microorganizational research: An investigation of prevalence and effect." *Journal of Applied Psychology*, 79(1), 1994, pp. 67-76.

Feldman, J. M. and Lynch, J. G. "Self-generated validity and other effects of measurement on belief, attitude, intention, and behavior." *Journal of Applied Psychology*, 73(3), 1998, pp. 421-135.

Hufnagel, E. M. and Conca, C. "User response data: The potential for errors and biases." *Information Systems Research*, 5(1), 1994, pp. 48-73.

Jackson, D.N Acquiescence response styles: Problems of identification and control. In I.A. Barg (Ed.), *Response set in personality assessment.* Chicago, IL: Aldine, 1967.

Kemery, E. R. and Dunlap, W. P. "Partialling factor scores does not control method variance: A reply to Podsakoff and Todor." *Journal of Management*, 12(4), 1982, pp. 525-544.

Lewis, W., Agarwal, R., and Sambamurthy, V. "Sources of Influence on Beliefs about Information Technology Use: An Empirical Study of Knowledge Workers." *MIS Quarterly*, 27(4), December, 2003, pp. 657-678.

Lindell, M. K. and Whitney, D. J. "Accounting for common method variance in cross-sectional research designs." *Journal of Applied Psychology*, 86(1), 2001, pp. 114-121.

Malhotra, N. K., Kim, S. S., and Patil, A. "Common Method Variance in IS Research: A Comparison of Alternative Approaches and a Reanalysis of Past Research." *Management Science*, 52(12), December 2006, pp. 1865-1883.

Moore, G. C. and Benbasat, I. "Development of an instrument to measure the perceptions of adopting an information technology innovation." *Information Systems Research*, 2(3), 1991, pp 173-191.

Podsakoff, P M., MacKenzie, S. B., Lee, J.Y., and Podsakoff., N. P. "Common method biases in behavioral research: A critical review of the literature and recommended remedies." *Journal of Applied Psychology*. 88(5), 2003, pp. 879-903.

Rorer, L.G. The great response-style myth. *Psychological Bulletin, 63,* 1965, pp. 129-156.

Spector, P. E. "Method Variance in Organizational Research: Truth or Urban Legend?" *Organizational Research Methods*, 9, 2006, pp. 221-232.

Straub, D, Boudreau, M. C., and Gefen, D."Validation guidelines for IS positivist research." *Communications of the Association of Information Systems*, 13, 2004, pp. 380-427.

Watson D, Clark LA, Tellegen A. "Development and validation of brief measures of positive and negative affect: the PANAS scales." *Journal of Personality and Social Psychology*. 54(6), June 1988, pp. 1063-70.

Appendix B
Other Survey Items

Construct	Items	Source
Computer Self-Efficacy	SE1: I feel confident in my ability to use the Blackboard website SE2: I am able to effectively use the Blackboard website to obtain the information I need	Compeau and Higgins, 1995
Ease of Use	EOU1: My interaction with Blackboard is clear and understandable EOU2: I find it easy to get Blackboard to do what I want it to do EOU3: Overall, I believe that Blackboard is easy to use EOU4: Learning to operate Blackboard is easy for me	Moore and Benbasat, 1991
Relative Advantage	RA: Blackboard enables me to accomplish my school tasks more quickly RA2: Blackboard makes it easier to do my schoolwork RA3: Blackboard enhances my effectiveness in doing my schoolwork RA4: Blackboard gives me greater control over my schoolwork	Moore and Benbasat, 1991

Appendix C
Un-manipulated Sources of CMB

Source of CMB	Items	Item Source
Consistency motif	SNCOPIIT1: Compared to (other student), I would be more likely to look for ways to experiment with new information technology SNCOPIIT2: Compared to (other student), I'm usually the first to try out new information technologies SNCOPIIT3: Compared to (other student), I am more eager to try out new information technologies SNCOPIIT4: Compared to (other student), I like to experiment more with new information technologies	Adapted from Agarwal and Prasad (1998)
Social desirability	COPIIT1: If (other student) heard about a new information technology, s/he would look for ways to experiment with it COPIIT2: Among our peers, s/he is usually the first to try out new information technologies COPIIT3: In general, s/he is eager to try out new information technologies COPIIT4: S/he likes to experiment with new information technologies	Adapted from Agarwal and Prasad (1998)

Appendix A
Manipulation of PIIT

	Baseline	Ambiguous	Negatively Worded	Item Embeddedness	Item Priming	Scale Format
Scale format	1-Strongly Disagree, 2-Disagree, 3-Neither Agree, Nor Disagree, 4-Agree, 5-Strongly Agree					-3 to +3
Introduction to the section	For the following questions, please indicate the extent to which you agree with the following statements.				This next section of questions is going to focus specifically on your own level of innovativeness. In other words, how innovative do you think that you are? Answering more positively indicates that you feel that you are more innovative.	When a new information technology comes out, I…
PIIT1	If I heard about a new information technology, I would look for ways to experiment with it.	If I heard about a new information technology, I would look for ways to experiment with it.	If I heard about a new information technology, I would look for ways to experiment with it.	If I heard about a new information technology, I would look for ways to experiment with it.	If I heard about a new information technology, I would look for ways to experiment with it.	Do not actively look for ways to experiment with it/ Actively look for ways to experiment with it
PIIT2	Among my peers, I am usually the first to try out new information technologies.	Among my peers, I am usually the first to play around with, try out, and experiment with new information technologies.	Among my peers, I am usually the last to try out new information technologies.	Among my peers, I am usually among the first try out new information technologies	Among my peers, I am usually the first to try out new information technologies.	Am among the last to try out/ Am among the first to try out
PIIT3	In general. I am eager to try out new information technologies.	In general. I am eager to try out new information technologies.	In general. I am eager to try out new information technologies.	In general. I am eager to try out new information technologies.	In general. I am eager to try out new information technologies.	Am hesitant to try out/ Am eager to try it out
PIIT4	I like to experiment with new information technologies.	I like to experiment with, try out, and play around with new information technologies.	I do not like to experiment with new information technologies.	I like to experiment with new information technologies.	I like to experiment with new information technologies.	Do not like to experiment with it/ Like to experiment with it