Appendix 1: Correlation

Table A1: Correlation Matrix												
Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
1. BI&A-SE	1											
2. FP	-.11	1										
3. OP	-.39***	.35	1									
4. FFP(HAL)	-.14**	.22	.07	1								
5. FOP(HAL)	-.24***	.26	.38***	.45***	1							
6. FFP(SAL)	-.14**	.18	.20	.34***	.25***	1						
7. FOP(SAL)	-.01	.12	.38	.20***	.43***	.34***	1					
8. RoR	.03	.14**	.56***	.06	.19***	.08	.06	1				
9. Medicaid	.09	.26***	.12**	.19***	-.03	.11	.19***	.14**	1			
10. Casemix	-.19***	-.02	.47***	.19***	.38***	-.01	.19***	.13**	.13**	1		
11. Hosp Size	.14**	-.01	-.25**	.05	-.15**	-.02	.04	-.08	.06	.23**	1	
12. City Size	-.08	-.07	-.12**	.13**	-.02	-.02	.13**	-.06	.05	.35**	.63**	1

Note: (1) **p≤0.05; ***p≤0.001, (2) BI&A-SE: BI&A-enabled Search Effort, Financial Performance (FP), Operational Performance (OP), RoR: Rate of Reimbursement, FFP (H/SAL) and FOP (H/SAL): Failures in Financial and Operational Performance relative to Historical/Social Aspirational Level.

Appendix 2: Diagnostics and Robustness Checks

Diagnostics checks using Breusch and Pagan's Lagrangian multiplier test ($p \leq 0.05$) and the Hausman test ($p \leq 0.05$) indicated that the fixed effect model (FEM) is more appropriate from a statistical perspective. Given the panel nature of the data, one could anticipate panel-specific heteroscedasticity due to variance of errors across each hospital. Results from likelihood test (χ^2 (264) = 55.79, p>.05) indicated no presence of panel-specific heteroscedasticity. For further robustness, we conducted a modified Wald test (χ^2 (7) = 108.03, p<.05) which indicated presence of heteroscedasticity. Therefore, to control for unsuspected heteroscedasticity, we employed FEM with robust standard errors clustered to panel-specific identifiers as our main analysis. However, one could argue that BI&A-enabled search could be exogenously determined, which can complicate our empirical estimation. Therefore, we also report random effect model (REM) as an auxiliary comparative analysis (Model 4, Table 3). As mentioned earlier, random effects analysis will also allow us to test H5 to see the differences between sustained failure and not sustained failure clusters of firms and complement our finite distributed lag models (FDLM). The results from the REM are consistent with the findings from the FEM.

Results for the FDLM analyses reported in Table 4 are sensitive to the length of lags. Therefore, to determine the length of lags, we employed Akaike Information Criteria (AIC) and Final Prediction Error (FPE) analyses. Both analyses indicated a lag selection of eight, suggesting that eight lag periods be included in the FDLM (Akaike 1974; Kmenta 1971). Furthermore, we performed robustness checks against validity threats arising from multicollinearity, outliers and influential observations. All the results indicate a good fit for the model. The highest variance inflation factor was 7.4, which is below the acceptable levels (<10), suggesting that multicollinearity is unlikely to be a concern (Hair et al. 2006; Kennedy 2003).

Even though we have found sufficient evidence to support our proposed theory, we further tested additional models to attenuate any concerns regarding sample size and predictability power of the model. While retrospective post-hoc power analysis may not be useful at this stage, we performed other robustness checks. We re-analyzed our main model with random sampling at 70%, 80% and 90% of the data used in testing the main model. Even with relatively smaller sample size, all the results were consistent with the main model.

Further, our examination of the relationship between performance and BI&A-enabled search efforts can be subject to endogeneity issues. For instance, prior studies show that BI&A use is positively related to performance improvements (Kitchens et al. 2018; Saldanha et al. 2017); in contrast, this study theorizes for the effects of performance failures on BI&A enabled search viz. *ad-hoc* BI&A use. Therefore, any possible reverse causality can violate the exogeneity assumptions and residuals correlated with independent variables inducing biases (Allison 1990; Greene 2000). We inspect for this potential endogeneity in two ways.

First, we employ the Arellano-Bond generalized method of moments (AB-GMM) estimator, which utilizes the lagged values of endogenous variables’ first–difference as instrument variables (IV) (Arellano 2003; Arellano and Bover 1995). The system GMM estimator is particularly suitable in cases where instruments are absent, panel datasets are unbalanced, presence of autocorrelation and where independent variables may not be strictly exogenous (Labra and Torrecillas 2018; Roodman 2009). GMM is nonbiased and efficient in the presence of fixed effects and any endogenous variables. This also complements the REM (Table 3). To limit any biases in system GMM estimation induced by the IVs, we limit our treatment of endogeneity to OP and its related interactions (Labra and Torrecillas 2018; Roodman 2009). Following prior literature, we use Windmeijer's correction from downward biases in standard errors and then test our main model using a two-step system GMM estimator that is robust to autocorrelations and heteroscedasticity to obtain the estimates (Roodman 2009; Windmeijer 2005). Table A2, Model 1 reports the results from this approach. To further attenuate any concerns on endogeneity, we conducted multiple postestimation analyses. The results from the Arellano-Bond test (z = -.38, $p > 0.05$) fail to reject the null hypothesis that there is no autocorrelation of AR(2). Hansen's test of overidentification also fails to reject the null hypothesis, indicating that the instruments are exogenous (χ^2 (265) = .44, $p > .05$), and difference-in-Hansen's test of exogeneity fails to reject the null hypothesis, indicating that the subset of instruments used in the level equations are exogenous (χ^2 (264) = .45, $p > .05$).

Second, using second lags of the regressor as an IV, we estimate a 2-stage least squares (2SLS) analysis. Recent studies show that instead of relying on external IV, second lags of regressor can be employed in the treatments of endogeneity of error terms (Havakhor et al. 2019; Mithas and Rust 2016; Reed 2015). Similarly, we use a second lag of OP as the IV for OP and estimate a 2SLS to test the validity of our main model (Table 3, Model 3). Table A2, Model 2 reports the result from the 2SLS analysis. Although using only one IV limits us from examining overidentification of the exogeneity of instruments, we attenuate this concern by including multiple OP instruments. Following Lewbel (2012) and Baum et al. (2012), we employ a heteroscedastic covariance restriction to create internal instruments that are not subject to the instrument validity issues. Similar to prior research (Susarla et al. 2016), we use the second lag of OP and Lewbel's internal instrument of OP as our two instruments in a system GMM estimation. Because this approach uses a latent-variable method, it is also suitable when external instruments are unavailable (Susarla et al. 2016). Table A2, Model 3 report the results from this approach. As this approach uses multiple instruments, we tested for overidentification concerns through Sargan's test for overidentification. The analysis failed to reject the null hypothesis, indicating that the set of instruments used in the analysis are exogenous to error terms ($p > 0.05$).

Table A2: Additional Tests to Address the Issue of Endogeneity

DV: BI&A-SE	Model 1		Model 2		Model 3	
Instrument Variable Approach	AB-GMM (AR2)		Instrumented 2SLS: 2nd Lag Operational Performance		Heteroscedastic Covariance Restriction Method	
Main Effects	Coeff.	S.E	Coeff.	S.E	Coeff.	S.E
FP *(H1)*	-.318***	.055	-.364**	.129	-.347**	.111
OP *(H2)*	-.466***	.128	-.676***	.162	-.596***	.130
FFP (HAL)	-.155**	.076	-.291***	.074	-.296***	.073
FOP (HAL)	-.245***	.034	-.216**	.087	-.202**	.082
FFP (SAL)	-.148	.113	-.227	.190	-.222	.190
FOP (SAL)	-.019	.079	-.05	.248	-.008	.239
Interaction Effects						
OP * FP *(H3)*	.338***	.063	.396**	.128	.377**	.130
OP * FFP (HAL) *(H4a)*	.195**	.096	.321***	.084	.330***	.083
OP * FOP (HAL) *(H4b)*	.289**	.096	.225**	.103	.194**	.089
OP * FFP (SAL) *(H4c)*	.287**	.052	.219**	.126	.237**	.124
OP * FOP (SAL) *(H4d)*	.187**	.081	.329**	.237	.246	.214
OP * Sustained Failure *(H5)*			.543**	.181	.516**	.174
Control Variable						
Rate of Reimbursement	-.017	.069	.100	.069	.101	.070
Medicaid	.042	.079	-.083	.074	-.073	.072
CaseMix	.008	.086	-.127	.084	-.156**	.070
Hospital Size			.081	.061	.092	.058
City Size			-.140**	.068	-124**	.063
R^2			.341		.344	

Wald's χ^2	382.32	208.87	
N	260	263	263
Results Compared to Main Model	Consistent	Consistent	H4d not supported
Note: * p≤0.1; **p≤0.05; ***p≤0.001. BI&A-SE: BI&A-enabled Search Effort, Financial Performance (FP), Operational Performance (OP), HAL: Historical Aspirational Level. SAL: Social Aspirational Level. FFP (H/SAL) and FOP (H/SAL): Failures in Financial and Operational Performance relative to Historical/Social Aspirational Level.			

Appendix 3: Additional Models with Alternative Specifications and Measures

We performed a series of additional tests to add further robustness to our findings. Table A3 provides the results from these analyses. First, we examined the results from our main model by using individual measures of BI&A-enabled search construct. Model 1 provides the results when number of *ad hoc* reports is used as a primary dependent variable. Model 2 provides the results when the CPU time of *ad hoc* reports is used as a primary dependent variable. Model 3 shows the results when Disk I/O of *ad hoc* reports is used as a primary dependent variable. We did so to check whether the analyses differed significantly when individual measures were employed, as shown in prior research (Devaraj and Kohli 2003). Prior research has found mixed findings when aspiration-related constructs are operationalized as a spline function and continuous measures (Posen et al. 2018). Therefore, we further tested our findings using continuous measures of historical aspirational levels and social aspirational levels in Model 4, and employing net patient revenue per day (NPRDAY) as our primary FP in Model 5. Expect for H4d that is not supported in Model 1 and Model 4, the remaining results from the other models are consistent with the main results.

In addition to using alternative measures, we further supplement our test with different model specifications to check for consistency with our main results. We do so by introducing the interaction terms hierarchically to check for any changes in support of our hypotheses. Models 6 to 10 provide the results. The results from all five models in Table A3 converge with our main findings, indicating that the results of the main model are robust to different specifications.

Table A3: FEM-RSE Models with Alternative Measures and Specifications										
	Model 1		Model 2		Model 3		Model 4		Model 5	
Alternative Construct Measures	No. of ad hoc Reports		CPU Time of ad hoc Reports		Disk I/O of ad hoc Reports		Continuous Measure for HAL and SAL on BI&A-enabled Search		Net Patient Revenue per Day (NPRDAY) as Financial Performance	
Main Effects	*Coeff.*	*S.E*	*Coeff.*	*S.E*	*Coeff.*	*S.E*	*Coeff.*	*S.E*	*Coeff.*	*S.E*
FP *(H1)*	-.286**	.126	-.390**	.080	-.437**	.088	-.340**	.095	-.011***	.122
OP *(H2)*	-.538***	.109	-.617**	.150	-.649**	.145	-.664**	.214	-.587**	.138
FFP (HAL)	-.225**	.074	-.230**	.092	-.272**	.086	-.266**	.062	-.231**	.089
FOP (HAL)	-.041	.077	-.214***	.022	-.205***	.030	-.218***	.025	-.210***	.022
FFP (SAL)	-.178	.137	-.207**	.077	-.212**	.074	-.192**	.071	-.195**	.071
FOP (SAL)	-.023	.166	-.015	.066	-.037*	.062	-.025	.072	-.058	.052
Interaction Effects										
OP * FP *(H3)*	.386**	.129	.407**	.111	.444**	.111	.340**	.087	.423**	.108
OP * FFP (HAL) *(H4a)*	.213**	.091	.254**	.130	.297**	.127	.309**	.086	.270**	.115
OP * FOP (HAL) *(H4b)*	.115**	.058	.271**	.108	.270**	.115	.290**	.123	.249**	.102
OP * FFP (SAL) *(H4c)*	.202**	.097	.141**	.058	.161**	.065	.225**	.086	.139**	.055
OP * FOP (SAL) *(H4d)*	.089	.150	.252**	.093	.278**	.100	.118	.067	.279**	.097
Control Variable										
Rate of Reimbursement	-.001	.103	-.026	.102	-.017	.122	.024	.104	-.029	.108
Medicaid	-.019	.098	.134	.137	.155	.152	.087	.109	.099	.122
CaseMix	-.107	.071	-.123	.138	-.115	.145	-.085	.136	-.099	.130
Organizations	7		7		7		7		7	
Time Period										
N	269		269		269		269		269	
R^2										
Within	.224		.20		.224		.21		.211	
Between	.17		.557		.55		.556		.663	
Overall	.182		.283		.30		.302		.327	
Results Compared to Main Model	H4d not supported		Consistent		Consistent		H4d not supported		Consistent	

Note: * p≤0.1; **p≤0.05; ***p≤0.001. BI&A-enabled Search Effort is the dependent variable. Financial Performance (FP), Operational Performance (OP), HAL: Historical Aspirational Level. SAL: Social Aspirational Level. FFP (H/SAL) and FOP (H/SAL): Failures in Financial and Operational Performance relative to Historical/Social Aspirational Level.

Table A3: FEM-RSE Models with Alternative Measures and Specifications (Cont.)										
Hierarchical Introduction of Interaction Terms	Model 6		Model 7		Model 8		Model 9		Model 10	
Main Effects	*Coeff.*	*S.E*	*Coeff.*	*S.E*	*Coeff.*	*S.E*	*Coeff.*	*S.E*	*Coeff.*	*S.E*
FP *(H1)*	-.500**	.098	-.363**	.084	-.442***	.076	-.423***	.065	-.414***	.074
OP *(H2)*	-.190	.130	-.378**	.082	-.462**	.099	-.505**	.121	-.587**	.138
FFP (HAL)	-.033	.031	-.354**	.077	-.248**	.079	-.249**	.084	-.231**	.088
FOP (HAL)	-.019	.062	-.032	.045	-.219***	.023	-.217***	.018	-.21***	.021
FFP (SAL)	-.164*	.078	-.179**	.063	-.186**	.070	-.195**	.069	-.194**	.071
FOP (SAL)	-.236**	.049	-.237***	.042	-.250***	.043	-.071	.056	-.057	.051
Interaction Effects										
OP * FP *(H3)*	.564**	.124	.359**	.072	.436**	.084	.431**	.092	.442**	.108
OP * FFP (HAL) *(H4a)*			.481***	.078	.327**	.087	.295**	.106	.269**	.115
OP * FOP (HAL) (*H4b*)					.281**	.084	.253**	.091	.248**	.102
OP * FFP (SAL) (*H4c*)							.248**	.075	.139**	.054
OP * FOP (SAL) *(H4d)*									.279**	.096
Control Variable										
Rate of Reimbursement	-.112	.111	-.026	.095	-.031	.100	.014	.094	-.028	.107
Medicaid	.155	.143	.106	.153	.119	.151	.113	.132	.098	.121
CaseMix	-.095	.127	-.083	.128	-.072	.129	-.108	.125	-.099	.129
Organizations	7		7		7		7		7	
Time Period										
N	269		269		269		269		269	
R^2										
Within	.076		.172		.187		.20		.22	
Between	.226		.453		.418		.591		.521	
Overall	.117		.237		.242		.289		.28	
Results Compared to Main Model	H2 not supported		Consistent		Consistent		Consistent		Main Model	

Note: * p≤0.1; **p≤0.05; ***p≤0.001. BI&A-enabled Search Effort is the dependent variable. Financial Performance (FP), Operational Performance (OP), HAL: Historical Aspirational Level. SAL: Social Aspirational Level. FFP (H/SAL) and FOP (H/SAL): Failures in Financial and Operational Performance relative to Historical/Social Aspirational Level.

REFERENCES

Akaike, H. (1974). A new look at the statistical model identification. *Automatic Control, IEEE Transactions on* 19(6):716-723.

Allison, P.D. (1990). Change scores as dependent variables in regression analysis. *Sociological Methodology* 20(1):93-114.

Arellano, M. (2003). *Panel data econometrics*. Oxford University Press.

Arellano, M., Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *J. of Econometrics* 68(1):29-51.

Baum, C.F., Lewbel, A., Schaffer, M.E., Talavera, O. (2012). Instrumental variables estimation using heteroskedasticity-based instruments *United Kingdom Stata User's Group Meetings*.

Devaraj, S., Kohli, R. (2003). Performance impacts of information technology: is actual usage the missing link? *Management Science* 49(3):273-289.

Greene, W.H. (2000). *Econometric Analysis* 3rd ed. Macmillan,, New York.

Hair, J.F., Tatham, R.L., Anderson, R.E., Black, W. (2006). *Multivariate data analysis*. Pearson Prentice Hall Upper Saddle River, NJ.

Havakhor, T., Sabherwal, R., Steelman, Z.R., Sabherwal, S. (2019). Relationships Between Information Technology and Other Investments: A Contingent Interaction Model. *Inform Systems Res.* 30(1).

Kennedy, P. (2003). *A Guide to Econometrics*. MIT Press.

Kitchens, B., Dobolyi, D., Li, J., Abbasi, A. (2018). Advanced Customer Analytics: Strategic value through integration of relationship-oriented big data. *J. Of Management Inform Systems* 35(2):540-574.

Kmenta, J. (1971). *Elements of Econometrics*. Macmillan New York.

Labra, R., Torrecillas, C. (2018). Estimating dynamic Panel data. A practical approach to perform long panels. *Revista Colombiana de Estadística* 41(1):31-52.

Lewbel, A. (2012). Using heteroscedasticity to identify and estimate mismeasured and endogenous regressor models. *J. of Business & Economic Statistics* 30(1):67-80.

Mithas, S., Rust, R.T. (2016). How information technology strategy and investments influence firm performance: Conjecture and empirical evidence. *MIS Quart.* 40(1):223-245.

Posen, H.E., Keil, T., Kim, S., Meissner, F.D. (2018). Renewing Research on Problemistic Search—A Review and Research Agenda. *Acad. of Management Annals* 12(1):208-251.

Reed, W.R. (2015). On the practice of lagging variables to avoid simultaneity. *Oxford Bulletin of Economics and Statistics* 77(6):897-905.

Roodman, D. (2009). A note on the theme of too many instruments. *Oxford Bulletin of Economics and Statistics* 71(1):135-158.

Saldanha, T.J., Mithas, S., Krishnan, M.S. (2017). Leveraging Customer Involvement for Fueling Innovation: The Role of Relational and Analytical Information Processing Capabilities. *MIS Quart.* 41(1).

Susarla, A., Oh, J.-H., Tan, Y. (2016). Influentials, imitables, or susceptibles? Virality and word-of-mouth conversations in online social networks. *J. of Management Inform Systems* 33(1):139-170.

Windmeijer, F. (2005). A finite sample correction for the variance of linear efficient two-step GMM estimators. *J. of Econometrics* 126(1):25-51.