# HRD Learning Participation: An Empirical Study of E-learning Completion

*Greg G. Wang, Diane Foucar-Szocki, and Oris Griffin*
*James Madison University*

*This study offers empirical evidence in HRD e-learning completion. Based on the Learning Participation Theory (LPT) (Wang & Wang, 2004), a study was conducted with U.S. corporate e-learners to explore the determinants of e-learning completion. The results generally confirmed the hypothesis by the LPT that individual, learning process, and organizational clusters, as well as environmental factors, as specified in the study, are significant determinants of e-learning completion. The implications of the results are also discussed.*

Keywords: HRD Learning Participation Theory (LPT), E-Learning Participation, E-Learning Completion

Rapid technology advancement has created a strong impetus and tremendous opportunities for human resource development (HRD) throughout all domains of organizations. E-learning, as rooted in computer media and internet technologies, has witnessed an exponential growth since the 1990s (Clark, 1999; Rosenberg, 2001). Some even declared it as "e-learning revolution" (Galagan, 2000, p. 25). However, a consensus appears to be the dearth of scholarly research on e-learning related topics. Welsh, Wanberg, Brown, and Simmering, (2003) conclude that the applications of e-learning in HRD move faster than scholarly empirical understanding of e-learning. A key difference between traditional HRD and e-learning interventions is the possibility for employees to individualize their learning experience and do what they want and when they want it (Filipczak, 1996). Such individualization has created a significant shift in learning responsibility from organization to employees because employees now control important aspects of learning, including participation, completion, or drop-out. Literature has noted that the shift toward learner control of HRD interventions demands a shift in research attention toward different learning behavior for learning outcomes (Ford & Kraiger, 1995; Ford, Smith, Weissbein, Cully, & Salas., 1998).

## Purpose and Significance of the Study

The early success of e-learning has been reflected in a number of reports, as reviewed and concluded by Russell (1999), there are no significant differences between distance learning and traditional classroom learning. More recent studies in higher education also confirmed that students could learn equally well in online courses (Lu, Yu, & Liu, 2003). However, those studies were drawn from learners who completed the entire learning as designed. What was not included were those who might start a learning program but discontinue before completion.

Popular press overwhelmingly reminded us of the low completion rates in the corporate world. According to a recent report, 70 percent of corporate learners do not complete scheduled online learning programs (Meister, 2002). Frankola (2001) claimed a 20 to 50 % of e-learning dropout rate. Murphy (2001) also cited 10% completion rate for online interventions. Unfortunately, no empirical study has been found through our review of literature that focuses on this issue. The problem seemed to be so pervasive that even popular press called for quantitative study for evidence of a widespread dropout problem for online HRD interventions in the corporate world (Zielinski, 2000).

The purpose of this study is to empirically explore HRD e-learning participation behavior and factors affecting the completion of HRD e-learning interventions based on the HRD learning participation theory (LPT) proposed by Wang and Wang (2004). Specifically, it is to answer the two research questions: (1) What is the e-learning completion rate in the corporate world? (2) What are the major factors that may contribute to e-learning completion?

To this end, the study fills a gap in empirical study of e-learning participation. Moreover, exploring factors that influence employee e-learning completion behavior can provide insight for organizations to formulate learning strategy and policy to manage and implement e-learning intervention more effectively and efficiently.

## Theoretical Framework

Wang & Wang (2004) proposed a theoretical framework, HRD Learning Participation Theory (LPT). As depicted in Figure 1, three clusters of factors were hypothesized surrounding and influencing employees' participation in HRD learning interventions: individual, learning process, and organizational. The clusters are mediated by environmental

factors. The individual cluster includes motivation, personal characteristics, learning style, learning technolog orientation, among others. The learning process cluster includes constructs ranging from instructional designdelivery platform, and instructional facilitation. Within the organization cluster, factors such as organizational support, organizational policies and regulations, are highlighted. Macro-environmental factors are also included in the framework, although their impact on learning has been noted to vary depending on specific situations.

The LPT model defines HRD learning participation at two levels, (a) whether to participate and by whom, and (b) whether to complete or drop out. This study examines empirically the participation issue at the second level to identify variables that affect individual learners completing an HRD e-learning intervention. Presumably, completion and drop-out are two aspects of the participation issue. Once engaged in a learning intervention, an employee may carry out the learning process to its completion or stop the learning process and drop out at any time before completion. This decision involves a rather complex process that may be affected by multidimensional factors during the learning process by individual and organizational factors.

## Method

A survey method was used to explore the e-learning participation relationships. We deployed a Web-based questionnaire to collect individual employees' data on e-learning participation behaviors and perceptions. Unable to measure all variables defined in Wang & Wang (2004), we focused on e-learning specific variables.

*Completion Rate*

Instead of directly asking reported completion or drop-out rate by individuals, we requested respondents to report the number of e-learning programs they have started and completed, respectively, in the past 3 years. For the purpose of comparison, we also measured traditional learning interventions in a similar way for the same time period. Calculated individual e-learning completion rate ranged from 0% to 100% and was used as the dependant variable in the subsequent analysis.


Figure 1. *A Conceptual Framework for Learning participation of HRD Intervention*

Based on the hypotheses proposed by Wang & Wang and our experience with e-learning practice. We specified the following variables under the question of "For the learning courses I take, the following factor(s) affected my completion" in the questionnaire survey. Guided by the LPT model, we group the variables into the following clusters, although the confirmation of the grouping is subject to further analysis, which will be presented subsequently.

*Individual cluster.* The variables under the individual factors were items that included motivation, learning style matching, and so forth (see Table 1). For learning technology orientation, we defined a variable, technical efficacy. Following Bandura's (1991) definition, technical efficacy is the confidence a learner has that s/he can learn the content with required technology. Similar to a Likert 5-point scale, the variable ranged from extremely uncomfortable (coded as -2) to extremely comfortable (coded as 2). Other variables on individual characteristics, such as age, education background, and industry, were also included.

*Learning process cluster.* Learning process cluster is a key to differentiate the LPT from other models related to learning participation in related fields (Wang & Wang, 2004). We specified variables affecting elearning completion as e-learning interaction attractiveness, learner interactions, instructor and administrative follow-ups, learning time, and learning at home vs. at work in the survey.

*Organization cluster.* The LPT model posits that organization factors may either promote or hinder HRD learning participation. To reflect such relationship, several variables regarding organization support were incorporated in the survey, including supervisor and administrative follow-up, organization policy requirement for completion, provisions of incentive for completion, and changes in work hours during the e-learning process.

*Environmental factors.* Individual perceived completion rate in the organization as identified, as an environmental variable. Presumably, if e-learners perceives a high completion rate in their organizations, regardless of actual completion rate, they are more likely to complete the e-learning interventions, and vice versa. At the initial data collection process, the survey was sent to a small group of selected e-learners to pilot-test its feasibility. Feedback was used to revise and improve the accuracy and format of the survey. The pilot survey data was not included in the final analysis.

Due to cost constraints and the limitations in accessing target participants, we defined the sampling frame of the study as members participating in online HR/HRD communities in the U.S. All major online HRD communities were identified, including discussion forums and online HRD communities of practice such as HRNet, ODNet,
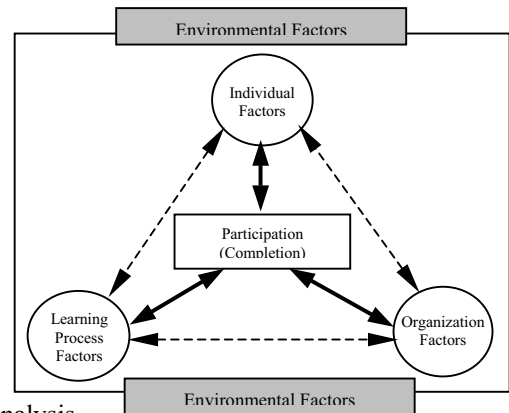
ROInet, TRDEV, etc. Announcement and call for participation of the study were sent to the online HR/HRD communities requesting those located in the U.S. respond to the questionnaire deployed on a designated website. At the conclusion of the data collection, we received 555 responses, among which, 157 were completed by respondents outside of the U.S. thus were not included in the study. The remaining 398 responses were confirmed through a defined country code in the database, and monitored through the respondents' IP addresses for data accuracy.

In addition, responses that fell into one or more of the following criteria were considered invalid and excluded from the analysis: (1) responses indicating that the participant had completed more e-learning courses than they had started because completion rate cannot exceed 100%; (2) responses indicating the participant had not started an e-learning course within the last three years; and (3) more than 20% of the items were left unanswered; (4) the reported number of course completion is more than 30 in the past 3 years. For criterion (4), We consider those e-learners were full time students in a degree program; whereas the study is focused on fulltime employees involving in HRD related e-learning interventions on a part-time bases. The final valid samples after the treatment resulted in a total of 363 responses.

*Nonresponse Bias and Missing Data*

To overcome the self-selection nature of the survey responses, a non-response bias analysis was conducted after the conclusion of the data collection. We randomly selected 50 U.S. members on the lists of the online communities in the frame and sent them the same questionnaire via an email attachment. We received 12 completed responses. With the same criteria discussed earlier. We found the characteristics of the follow-up respondents were similar to those in the major dataset. The small group's responses were therefore combined with the larger one, totaling the final observations 375.

The data collection process did not allow for a determination of the percentage of respondents from within the participating HRD online communities, although the percentage was relatively low. The potential low response rate may be caused by the following reasons. While the HRD online communities we chose for the study were relatively large, the actual participating members in daily discussions usually did not exceed 5% of the overall members. According to Krosnick (1999) and Dillman (1991), low response rates alone do not necessarily suggest bias when respondent characteristics are representative of nonrespondents. We encountered less than 2% of missing data in item responses after imposing the 4 criteria for valid responses. Downey and King (1998) recommend that, when the number of items missing was 20% or less, using item mean or person mean techniques for replacing missing data is able to yield good representations of the original data. We used item mean technique to treat the missing item responses as suggested by Downey and King (1998).

The internal consistency for both dichotomous (Yes or No) and Likert-scale response to the surveyed items was analyzed with the Kuder-Richardson coefficient (K-R-20=0.43), and appeared to be modest reliable for the variables measured. The coefficient alpha for Respondents' self-efficacy regarding e-learning related technology was 0.78, suggesting a reasonable internal consistency for the measure. Additionally, the model construct, and the adequacy of the variables and clusters specification need to be further verified. Factor analysis was conducted to identify whether the latent variables have a factor structure as hypothesized by the LPT theory. Because of the explorative nature of the study, an exploratory factor analysis (EFA) is conducted to explore the data, as the model has not been quantitatively tested except a qualitative investigation (Wang & Wang, 2005).

## Results

*Preliminary Analysis*

*Completion rate.* From the reported number of programs started and completed, we used the following method to estimate the completion rate (CR): CR=(Course Completed)/(Course Started) x 100%. We found that e-learning completion rate was 74 percent for the past 3-year period. The mean number of started online programs is 5.4 with a standard deviation (STD) of 5.4 and the mean number of completed online programs is 4.0 with STD of 4.3. In contrast, traditional program reached 98 percent of completion rate (See Table 1). Clearly, the e-learning completion rate is lower than traditional learning interventions. Yet, the e-learning completion rate found in this study is still much higher than those reported in popular press. A possible explanation might be that the samples of the study were from online communities, and they were more familiar with the technical environment of e-learning. However, given the U.S. internet penetration at close to 70 percent of the population as reported by Miniwatts International (2005), we may also be convinced that the rest of the population, especially the workforce at professional level, in the country have the required technical environment to engage in e-learning. This trend can also be observed in the latest State of the Industry by ASTD (Sugrue & Kim, 2004). Interestingly, with the 74 percent completion rate by the respondents, we found that respondents' individual perception of completion rate in their organizations were only 38.8 percent. This may provide insight in differences between actual completion rate and that anecdotally

perceived. Thus we may conclude that the overwhelmingly low completion rate previously reported at least exaggerated, to some degree, the low completion rate in e-learning reality. Table 1 reports descriptive statistics from the survey.

*Factor Analysis*

Only latent variables of the data were included in the factor analysis. Initially, Motivation (Motivat) as an individual variable and Incentive (Incent) as an organizational variable were included in the factor analysis. These two variables were found cross-loaded on more than one factor. According to the suggestion in literature (Hutcheson & Sofroniou, 1999; Pett, Lackey, & Sullivan, 2003), the variables were dropped from the factor analysis. In fact, cross loading for motivation may be expected under given variable specification, because almost all other variables remained included a certain aspect related to motivation to learn. The cross loading for the variable Incent may be caused by its potential overlap with the variable Policy.

After much iteration in exploring and comparing different factor combinations and resulting statistics, the final solution displayed a four-factor structure. Table 1 reports the factor analysis result.

The factor structure identified revealed noticeable pattern of the theoretical hypotheses by the LPT model, except for the variable of administrative followup, Admfoll, which appeared to be loaded incorrectly. Given the dichotomous nature of the variable scale, it may suggest that further investigations on the variable specification and scale are needed. On the other hand, administrative follow-up may indeed be considered as an environmental variable for e-learning as it seemed not quite fit into any of the three clusters defined. Nonetheless, as an explorative study, we retained this variable for regression analysis.

Table 1. *Rotated factor loadings for e-learning participation clusters*

| Variable | Individual | Learning Process | Organizational | Environmental | Communality (R²) |
|---|---|---|---|---|---|
| Lnstyle | 0.49 | | | | 0.24 |
| Techeff | 0.54 | | | | 0.30 |
| Studytm | 0.47 | | | | 0.40 |
| Stuinter | | 0.73 | | | 0.59 |
| Eintera | | 0.49 | | | 0.30 |
| Lnathome | | -0.93 | | | 0.89 |
| Lnatwork | | -0.91 | | | 0.88 |
| Workhrs | | | -0.44 | | 0.57 |
| Insfoll | | 0.69 | | | 0.53 |
| Supfoll | | | 0.44 | | 0.31 |
| Admfoll | | | | 0.65 | 0.48 |
| Policyr | | | 0.45 | | 0.28 |
| Estcomprs | | | | 0.68 | 0.48 |
| Eigenvalue | 2.04 | 1.96 | 1.39 | 1.22 | |
| Percentage of Variance | 14.6 | 14.0 | 9.9 | 8.7 | |

*Regression Analysis*

Multiple regression was conducted using the results from the factor analysis to further investigate e-learning participation relationship. Because of the correlation nature of the factor analysis, we first examined potential multicollinearity threats among the independent variables. A zero-order correlation analysis found that the correlation coefficients among the variables were mostly ranging from 0.00 to 0.25, indicating a minimum level of correlation among the independent variables (correlation matrix is not presented due to space constraints). Two variables, Lnathome and Lnatwork, displayed a moderate correlation at r=-0.51, which was well below the 0.85 threshold of multicollinearity as recommended by Kline (1998). Therefore, the preliminary results from the factor analysis were considered acceptable for regression analysis. To gain a better understanding of the determinants of e-learning, we also included demographic variables such as Age, Gender, Education, and Industry in the regression analysis.

The findings from the regression analysis further confirmed that HRD e-learning intervention participation and completion are surrounded by the three clusters of variables hypothesized by the LPT model. The regression results are presented in Table 2.

Within the individual cluster, perceived learning style matching (LNSTYLE) appeared to be a significant factor influencing completion rate (14.05, p < .01). In other words, those who perceived a high degree of learning style matching with the programs engaged were more likely to complete. This finding added a controversial aspect to current literature, which seemed to be inconclusive on learning impact. For example, some studies (Larsen, 1992; Lu, Yu, & Liu, 2003; Martinez and Bunderson, 2000) reported no significant impact of learning styles on learning behavior and outcomes; others (Smith & Hardaker, 2000) observed that learning styles were directly related to learning involvement and participation. Yet, all empirical studies on learning style were conducted in higher education settings and their relevancy and applicability to HRD learning interventions is unknown. Further research is needed to explore the relationship between e-learning behavior and learning styles, especially in HRD practices.

Surprisingly, technology self-efficacy (TECHEFF) was not significant in determining e-learning completion rates. This finding is seemingly inconsistent with previous studies. For instance, Gist, Schwoerer, and Rosen. (1989) and Martocchio (1994) suggested a positive association between levels of technical efficacy and learning

outcomes. The inconsistency may be caused by two reasons. (1) Difference in study focus. This study is among the first focusing on learning participation while other studies are addressing learning outcomes with technology; and (2) Difference in sample pools. The samples for this study were from online community members, who might already be competent in technology in order to participate in online activities. Other studies used samples from university service and administrative employees who may not be as technically competent. Nonetheless, further research is needed to explore the relationship between technical efficacy and e-learning participation behaviors.

One of the benefits offered by e-learning is the convenience to learning and its accessibility (e.g., Welsh, et al., 2003). It is often referred to as the possibility of learning anytime, anywhere. However, it may also present a challenge to learners that they must learn among distractions, and increased workloads. This can be seen from estimated coefficients for the variables of STUDYTM and WORKHRS. Negative and significant coefficient for WORKHRS (-5.818, p < .05) implied that employees engaged in e-learning often under increased or the same workload during the learning process, which would reduce the likelihood for them to complete the learning. Meanwhile, study time (STUDYTM) was found to positively and significantly determine e-learning completion rate.

In the Learning Process cluster, two variables, learner interaction (STUINTER) and e-learning interactive attraction (EINTER), were positive and significant with respect to completion rate. The result may be among the first empirical evidence linking instructional design elements with e-learning participation and outcome, although a number of studies have proposed conceptual framework that hypothesized such relationship (e.g., MacDonald & Gabriel, 1998; MacDonald, Stodel, Farres, Breithaupt, & Gabriel, 2001). This suggested the importance of designing interactive online learning experiences and its contributions to e-learning completion. Instructor's follow-up (INSTFOLL), together with administrative follow-up (ADMFOLL), is also found to be a significant factor that may encourage employees complete the learning process.

In terms of learning locations, although employees did have the luxury of participating in e-learning anywhere, the variable LNATHOME is negatively associated with e-learning completion rate, indicating that learning location matters for e-learning participation and completion regardless of the possibilities that e-learning may offer. In other words, employees taking e-learning at home are less likely (-10.38, p<.05) to complete the HRD intervention they participated in. At the time work-life balance become an issue for many organizations (Hill, et al., 1998), it is understandable that taking e-learning at home would blur the boundary between work and family life.

At organizational level, organization policy requiring for completion (POLICYR) is significantly related to e-learning completion. This finding showed the important role that organization policies and regulations might play in supporting and encouraging employees' learning participation and completion. Furthermore, although recent years witnessed a growing body of literature in supervisor's role of facilitating workplace learning (Hughes, 2004; MacNeil, 2004; Spreitzer, et al., 1999), our result did not find a significant relationship between supervisor's follow-up and e-learning completion, although the estimated sign was in the right direction.

Table 2. *Multiple Regression Results for E-learning Completion*

| Variable | B | T | Data Type |
|---|---|---|---|
| TECHEFF | 0.77 | 0.68 | 1-5 scale |
| LNSTYLE | 14.05 | 3.09*** | Binary |
| STUDYTM | 0.46 | 1.97*** | Continuous |
| AGE | -0.19 | -1.21 | Continuous |
| GENDER | -15.31 | -1.46* | Binary |
| EDUCAT | -0.75 | -0.96 | Continuous |
| EINTER | 5.91 | 1.96** | Binary |
| INSTFOLL | 8.57 | 1.91** | Binary |
| ADMFOLL | 20.11 | 2.05** | Binary |
| STUINTER | 4.18 | 0.98 | Binary |
| LNATHOME | -10.38 | -1.78** | Binary |
| LNATWORK | -2.50 | -0.44 | Binary |
| WORKHRS | -5.82 | -2.08** | 1-3 scale |
| SUPFOLL | 1.01 | 0.13 | Binary |
| POLICYRQ | 7.74 | 2.35*** | Binary |
| ESTCOMPR | 0.80 | 7.96*** | Continuous |
| | | | *Base Category: Technology* |
| FIINRE | 13.58 | 3.20*** | Binary |
| MANUFSL | 0.01 | 0.34 | Binary |
| PROFSER | 7.20 | 1.71** | Binary |
| GOVERNMT | 9.71 | 1.22 | Binary |
| EDUCAT | 4.77 | 0.81 | Binary |
| Constant | 80.66 | 4.46*** | $R^2 = 0.29$ Adj $R^2 = 0.25$ |

*p<.10, ** p<.05, ***p < .01

As for the environmental variable, respondent's perceived organizational e-learning completion rate (ESTCOMPR) it is unlikely that all respondents were aware of the actual completion rate in their organizations. Therefore, the perceived completion rate indeed served as a macro environment that directly or indirectly influence their participation behaviors. This finding was supported by the relatively small but significant coefficient for ESTCOMPR (0.7988, p<.01). In other words, respondents who perceived a higher completion rate in their organizations would actually have a higher completion rate in e-learning. This finding support the hypothesis

posited in Wang & Wang (2004) on the influential role of environment on employee learning participation. Relating to the earlier discussion on completion rate. The discrepancy of completion rate between respondents perceived (33.8%) and actual completion rate found in this study (74%) may indicate that for any emerging challenges in HRD practice, scholarly research is needed to understand the real situation. If the analysis is true, we may argue that the media reported anecdotally based low e-learning completion rate have already created an environment that negatively impact on e-learning participation for individuals. At a minimum, speculations or hearsay without research justification can only create an environment that misleads the practice.

Respondents' industry characteristics displayed some interesting results. Those in professional services (PROFSER) and finance/insurance/real estate (FIINRE) were likely to complete e-learning, even more than those employed in technology industry (base category). An intuitive explanation may be that in industries where computer and Internet technology applications become a job requirement, employees generally tend to be more capable and comfortable to apply it in e-learning. However, due to the lack of representation of industries, the findings may not be generalized beyond the samples under study.

## Discussion

### Implications to HRD E-learning Practice

The findings of this study have important implications to HRD e-learning practices. It may provide insight to practitioners in formulating effective e-learning strategies for technology-based workplace learning.

While personal learning motivation is a critical factor determining an employee's persistence in learning participation, many other variables in learning processes and organizational levels may contribute to the motivation variable, hence can either reinforce or weaken motivational factor as revealed in the factor analysis. HRD practitioners may take advantage of such relationships through frequent follow-up with e-learning participants. Learning management via e-learning administration may also play a role in fostering a participation and completion culture. In addition, organizations may also encourage employee participation and completion of e-learning interventions through favorable policy requirement or learning incentives. Equally important to organizations is to support employees e-learning participation with specific on-the-job learning time to reduce interruption and distraction of the learning process. Assigning or releasing appropriate workload to employees who are engaged in e-learning could be another key factor to support employee learning. To avoid work-life conflict, organizations may consider discouraging employees engaging in e-learning at home during off work hours. By increasing workload and encouraging employee learning at home, the participation in e-learning may well be possibly turning the e-learning feature of "any time anywhere" to "*no time*" and "*nowhere.*" In short, in implementing HRD e-learning interventions, practitioners should pay close attention to integrating individual motivation, learning process support, and organizational support to ensure full employee participation and successful completion of e-learning.

### Implications to Further HRD Research

As a practice-oriented field, HRD encounters frequent challenges from daily practices. Many such challenges need to be addressed through theoretical and empirical studies rather than relying on prevailing anecdotal reports. A good example presented in this study is the difference in completion rate perceived by individual respondents and estimated actual completion rate of the respondents. This study is the first quantitative study to apply the LPT model proposed by Wang & Wang (2004) and explore e-learning participation in the form of completion behavior in HRD online communities. The study, through factor analysis, generally supports the constructs and the hypotheses by the LPT model that the three clusters form the determinants of employee learning participation. Further empirical investigations are needed to validate and improve the theoretical constructs in order to better understand workplace-learning participation, which is a precondition for learning interventions to create any business impact.

This study identified issues that require future research. Firstly, the factor structure, although promising and generally consistent with the hypothesized LPT model, need further exploration, especially for environmental factors. Secondly, the study did not find a significant relationship between technical self-efficacy and e-learning completion. While inconsistent with some intuitions in HRD practice (e.g., Welsh, et al., 2003), it may be due to the fact that the samples were drawn from a technically competent frame. It may also demonstrate that technical competency is a necessary, but not sufficient condition for employee to participate and complete an e-learning intervention. Further empirical study is needed to investigate this relationship. Thirdly, the result showed that learning style match is highly important to e-learning persistence, which is inconsistent with literature in higher education settings. Related empirical studies in HRD e-learning settings should be further conducted as this issue has important instructional design implications. Administrative follow-up role and the role played by environmental variables also need to be further explored.

Additionally, this study only explored e-learning participation behavior from a positive aspect, i.e., e-learning completion. The other side of e-learning participation, the drop-out issue, is equally important. It may be the case that the determinants of e-learning completion and drop-out are different to a certain degree. Drop-out studies may also have important implications to HRD practice.

*Limitations*

Although this study has provided some insights into HRD e-learning participation and completion, it is not without limitations. The study was based on voluntary participation of online HRD communities. The respondents were probably more technically astute than those outside the sample frame. Restrictions of range in some predictors may have occurred. For example, technical efficacy was found not associated with the completion rate, which may not be necessarily the case for a different group. Therefore, these results should not be generalized beyond HRD online communities without further research. Additionally, the study is focused on HRD learning participation rather than learning outcomes. Therefore, no learning effectiveness outcomes can be inferred from the results of the study.

## Conclusion

Based on the learning participation theory (LPT) proposed by Wang and Wang (2004), this study empirically investigated e-learning completion behavior in the HRD online community. Factor analysis results generally supported the theoretical construct of three clusters proposed by the LPT framework except for one potentially mis-loaded variable. We found that e-learning completion rate from the respondents is significantly higher than the respondents' perceived completion rate which may influenced by previously reported low completion rate in popular press. The regression analysis also supported that three clusters of variables, individual, learning process, and organizational determined the e-learning participation. The study offers some important practical and research implications, yet generalization of the results should be cautious due to the limitations of the study.

## References

Bandura, A. (1991). Social cognitive theory of self-regulation. *Organizational Behavior and Human Decision Processes*, 50, 248-287.

Bates, Holton, & Styler, (1996). Principles of CBI design and the adult learner: The need for further research. *Performance Improvement Quarterly*, 9, 3-24.

Clark, K. (1999). Virtual evolution. *Human Resource Executive*, *13*, 4, 32-33.

Crawford, S. D., Couoper, M. P., & Lamias, M. J. (2001). Web surveys: Perceptions of burden. *Social Science Computer Review*, *19*, 146-162.

Dillman, D. (1991). The design and administration of mail survey. *Annual Reviews of Sociology*, *17,* 225-249.

Dillman, D.(2000). *Mail and Internet surveys: The tailored design method* (2nd Ed.), New York: John Wiley & Sons.

Downey, R.. G., and King, C. V. (1998). Missing data in Likert ratings: a comparison of replacement methods. *The Journal of General Psychology, 125*(2), 175-187.

Filipczak, B. (1996). Training on the intranets: The hope and the hype. *Training, 33*(9), 24-32.

Ford, J. K. & Kraiger, K. (1995). The application of cognitive constructs and principles to the instructional system model of training: Implications for needs assessment, design, and transfer. In C. L. Cooper & I. T. Robertson (Eds.), *International review of industrial and organizational psychology* (pp. 1-48). New York: Wiley.

Ford, J. K., Smith, E. M., Weissbein, D. A. Cully, S. M., Salas E. (1998). Relationships of goal orientation, metacognitive activity, and practice strategies with learning outcomes and transfer. *Journal of Applied Psychology*, *83*, 218-233.

Frankola, K. (2001). Why online learners dropout. *Workforce, 10*, 53-63.

Galagan, P. A. (2000). The e-learning revolution. *T+D*, 54, December, 24-30.

Gist, M. S., Schwoerer, C. & Rosen, B. (1989). Effects of alternative training methods on self-efficacy and performance in computer software training. *Journal of Applied Psychology*, *74,* 883-891.

Hill, E. J ., Miller, B. C., Weiner, S. P., & Colihan, J. (1998). Influences of the virtual office on aspects of work and work/life balance. *Personnel Psychology, 51*(3), 667-683.

Hughes, C. (2004). The supervisor's influence on workplace learning. *Studies in Continuing Education*, 26, 275-287.

Hutcheson,, G. & Sofroniou, N. (1999). *The multivariate social scientist: Introductory statistics using generalized linear models*. Thousand Oaks, CA: Sage.

Judge, G., Hill, R., Griffiths, W., Lutkepohl, H. & Lee, T. (1988). *Introduction to the theory and practice of econometrics*, (2nd ed.). New York, NY: John Wiley & Sons.

Kline, R. B. (1998). *Principles and practice of structural equation modeling*. New York: Guilford.

Krosnick, Jon A. (1999). Survey research. *Annual Review of Psychology* 50:537-567.

Larsen, R. E. (1992). Relationship of learning style to the effectiveness and acceptance of interactive video instruction. *Journal of Computer-based Instruction*, *19*, 17-21.

Lu, J., Yu, C, Liu, C. (2003). Learning style, learning patterns, and learning performance in a WebCT-based MIS course. *Information & Management*, *40,* 497-507.

MacDonald, C. J. & Gabriel, M. A. (1998). Toward a partnership model for web-based learning. *The Internet and Higher Education, 1*(3), 203-216.

MacDonald, C., Stodel, E., Farres, L., Breithaupt, K. & Gabriel, M. (2001). The demand-driven learning model: A framework for web-based learning. *The Internet and Higher Education*, 4, 9-30.

MacNeil C.M. (2004). Exploring the supervisor role as a facilitator of knowledge sharing in teams. *Journal of European Industrial Training, 28*(1), 93-102.

Marquardt, M. J. and Kearsley, G. (1999). *Technology-based learning: Maximizing human performance and corporate success*. NY: St. Lucie Press.

Martinez, M. and Bunderson, C.V. (2000). Building interactive web learning environments to match and support individual learning differences. *Journal of Interactive Learning Research, 11*(2), 163-195.

Martocchio, J. J. (1994). Effects of conceptions of ability on anxiety, self-efficacy, and learning in training. *Journal of Applied Psychology, 79*(6), 819-825.

Meister, J. (2002). *Pillars of e-learning success*. New York: Corporate University Exchange.

Miniwatts International (2005). North America Internet Usage and Population. Retrieved August 21, 2005, from http://www.internetworldstats.com/stats2.htm#north

Murphy, H. L. (2001). E-learning put to the test: Companies have learned lessons online training. *Crain's Chicago Business*, *24,* 35.

Neter, J., Wasserman, W., & Hutner, M. H. (1990). Applied linear statistical methods (3$^{rd}$ Ed). Boston, MA: IRWIN.

Pitt, M. A., Nancy R. L. & Sullivan, J. J. (2003). *Making sense of factor analysis: The use of factor analysis for instrument development in health care research*. Thousand Oaks, CA: Sage.

Rosenburg, M. (2001). E-learning: strategies for delivering knowledge in the digital age. New York: McGraw-Hill.

Russell, T. (1999). *The no significant difference phenomenon*. Chapel Hill, NC: Office of Instructional Telecommunications, North Carolina State University.

Salas, E., Kosarzycki, M., Burke, C. S., Fiore, S. M. and Stone, D. L. (2002). Emerging themes in distance learning research and practice: Some food for thought. *International Journal of Management Reviews*, *4*, 135-153.

Smith, D. & Hardaker, G. (2000). E-learning innovation through the implementation of an internet supported learning environment. *Educational Technology and Society*, *3* (3), 422-432.

Spreitzer, G. M., De Janasz, S. C., & Quinn, R. E. (1999). Empowered to lead: the role of psychological empowerment in leadership. *Journal of Organizational Behavior, 20* (4), 511–526.

Sugrue B. and Kim, K. (2004), *State of the Industry: ASTD Annual Review of Trends in Workplace learning and Performance*. Alexandria, VA: American Society for Training & Development.

Wang, G. G. & Wang, J. (2004). Toward a theory of HRD participation. *Human Resource Development Review*, *3*(4), 326-353.

Wang, J., Wang, G. G., & Ruona, W. E. A. (2005). HRD Learning participation and outcomes: An empirical study. In M. L. Morris, F. M. Nafukho, & C. M. Graham (Eds.), *Proceedings of the 2005 Academy of Human Resource Development International Research Conference*, (pp. 709-716). Estes Park, CO: Academy of HRD.

Weible, R. & Wallace, J. (1998, Fall). Cyber research: The impact of the internet on data collection. *Market Research*, 19-24.

Welsh, E. T., Wanberg, C. R., Brown, K. G., & Simmering, M. J. (2003). E-learning: Emerging uses, empirical results and future directions. *International Journal of Training and Development, 7*(4), 245-258.

Zielinski, D. (2000). Can you keep learners online? *Training*, *37*(3), 65-75.