Communications of the Association for Information Systems

4-8-2021

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Abstract:

Digital learning platforms (DLPs) have emerged as highly effective tools to meet contemporary organizations' learning and knowledge-creation needs. Advanced information and communication technologies (ICT) embedded in these platforms create mobile learning workspaces that deliver ubiquitous yet targeted learning experiences. Scholars have shown a keen interest in assessing the success of DLPs, but most studies have examined only a specific aspect of DLP success. Current findings also show inconsistencies and contradictions that confound our understanding of this important topic. As a result, an integrated and accurate understanding of DLP success is missing. In this paper, we adopt rigorous meta-analytic procedures to consolidate extant findings and reconcile inconsistencies in our understanding of DLP success. Additionally, we extend our meta-analyses to investigate the contingency effects of two moderating variables—user context and cultural context. The results provide a more comprehensive and accurate understanding of DLP success. Our study contributes to the literature by extending the theory on DLPs and information systems (IS) success and by providing insightful recommendations for practitioners.

Keywords: Digital Learning Platforms, Information Systems (IS) Success, E-learning, Meta-analysis.

1 Introduction

Digital learning platforms (DLPs) constitute comprehensive bundles of IT capabilities such as machine learning, artificial intelligence, data mining, and gamification that enable organizations to deliver adaptive, targeted, and collaborative learning solutions (Hwang, Wu, Tseng, & Huang, 2011; Tiwana & Ramesh, 2001). The ongoing coronavirus disease of 2019 (COVID-19) pandemic has also highlighted the importance of DLPs as most organizations have transitioned their learning and talent development functions online[1]. Given the emerging relevance of DLPs, organizations and other stakeholders (e.g., platform developers and content developers) have a strong interest in assessing DLP success. A significant body of research has used DeLone and McLean's (2003) updated IS success model for this purpose. Although this literature has made valuable contributions, it still has three key limitations.

First, most studies have examined only one aspect of DLP success (Chen, 2010; Chen & Chengular-Smith 2015). Since the success dimensions embedded in the IS success model depend on one another, a selective examination of these dimensions fails to comprehensively explain DLP success. Thus, we lack an integrated view of DLP success. To help remedy this situation, we perform meta-analytic procedures to synthesize existing findings (2006-2019) and holistically explain DLP success.

Second, prior literature has found both significant and insignificant relationships among the same success dimensions (Arkorful & Abaidoo, 2015; Islam, Beer, & Slack, 2015). For example, some scholars have observed that system quality (Chuo, Liu, & Tsai, 2015; Yakubu & Dasuki, 2018), service quality (Chiu, Chiu, & Chang, 2007), and information quality (Yakubu & Dasuki, 2018) do not influence user satisfaction for DLPs. Other scholars have reported that system quality, information quality, and service quality do play a significant role in shaping user satisfaction (Alzahrani, Mahmud, Ramayah, Alfarraj, & Alalwan, 2019; Martins et al., 2019). Scholars also disagree on how different "use" indices shape the users' perceptions of net benefits for DLPs. The literature has also reported inconsistent findings about the influence that user satisfaction has on users' intention to use digital platforms (Yakubu & Dasuki, 2018). These inconsistencies create confusion about the key dimensions of DLP success. By conducting a rigorous meta-analysis of DLP-related studies, we reconcile prior inconsistencies and help develop a more accurate understanding of DLP success.

Third, learning is typically grounded in a learner's set of experiences, and DLP success may hinge on the context in which these platforms are implemented. For instance, a DLP used for higher education students may differ from a DLP used by an organization for its employees (Benson & Samarawickrema, 2009). Organizational users may use DLPs to achieve performance goals, which may shape their benefit expectations from these platforms differently from student learners, who may use DLPs to achieve their learning objectives. Such contextual differences between students and organizational users need to be explored to ensure that the universities (and businesses) that use such platforms focus on relevant parameters to ensure platform success in their unique context. Previous research has not examined issues pertaining to DLPs' user context.

Organizations deploy DLPs extensively across multiple global locations for online learning and virtual trainings. However, given significant cultural differences across various locations, using standardized DLPs across all locations may hurt their success. Access to technology and expectations of technology differ across cultures (Rai, Maruping, & Venkatesh, 2009; Venkatesh, Sykes, & Venkatraman, 2014), and these differences create a unique cultural schema that affects technology use and success. Prior studies have advocated that researchers examine the influence that different cultural contexts have on DLP success (Aparicio, Bacao, & Oliveira, 2016), yet no prior research has done so.

To fill these gaps, we conducted two additional meta-analyses to examine the moderating effects of the user context (student learners vs. organizational learners) and cultural context (Eastern vs. Western cultures). In doing so, we contribute to developing a more comprehensive and accurate understanding of DLP success. Our findings also contribute to the general IS success literature.

This paper proceeds as follows: in Section 2, we review the relevant literature and present the baseline hypotheses on DLP success. In Section 3, we discuss the moderation effects. In Section 4, we describe our research methodology. In Section 5, we present our findings. In Section 6, we discuss the study's implications and limitations. Finally, in Section 7, we conclude the paper.

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[1] We thank the associate editor for making this observation about DLPs' increasing relevance during the COVID-19 pandemic.

2   Background

2.1   Digital Learning Platforms

DLPs have disrupted the traditional learning paradigms in the last few years (Furió, Juan, Seguí, & Vivó, 2015). DLPs offer functionalities such as self-adapting computer simulations, realistic animation, computer-delivered reading comprehension, game-based learning, and massive open online courses (MOOCs) (Chauhan, 2017; Cidral, Oliveira, De Felice, & Aparicio, 2018). Contemporary DLPs use these functionalities to deliver a collaborative, individualized, and participatory e-learning experience (de Koning-Veenstra, Steenbeek, van Dijk, & van Geert, 2014). The propagation and growth of the World Wide Web and Internet of things (IoT) has enabled DLP service providers to offer learning experience globally via smartphones, laptops, and tablets. The ongoing coronavirus disease of 2019 (COVID-19) pandemic has also elevated DLPs from a viable learning alternative to mainstream learning and training management systems.

Two issues constrain current research on DLPs. First, DLPs bring together an extensive portfolio of innovative technologies, and a single research study lacks the bandwidth to assess the overall efficacy of these technologies to deliver learning successfully. Although individual studies have investigated DLP success (see Isaac, Aldholay, Abdullah, & Ramayah, 2019; Lin & Wang, 2012; Wang, Wang, Lin, & Tsai, 2019), a comprehensive understanding of DLP success is still missing. Second, inconsistent prior findings regarding DLP success necessitate a meta-analytic assessment to reconcile these inconsistencies. A meta-analytic assessment of prior findings would also help researchers develop a more accurate understanding of DLP success. Given the increasing importance of DLPs, a more accurate and comprehensive understanding of DLP success would promote future research inquisitions on DLPs and enhance their viability as mainstream learning and training management systems (Ozdamli & Uzunboylu, 2014).

2.2   IS Success

Researchers have proposed various models to examine the key outcome variable in IS research. DeLone and Mclean (1992) proposed their initial IS success model that identified information quality, system quality, user satisfaction, use, organizational impact, and individual impact as six key IS success measures. Seddon (1997) respecified this model by adding four novel variables (expectations, consequences, perceived usefulness, and net benefits to society) and reestablished the relationships between them. Later, Seddon, Staples, Patnayakuni, and Bowtell (1999) also proposed a matrix framework of IS effectiveness as an alternative to DeLeon and McLean's (1992) model.

Based on the extensive feedback that they received for their initial model, DeLeon and Mclean (2003) proposed an updated IS model with additional dimensions to measure IS success. This model best captures various DLP success dimensions and offers underlying theoretical arguments to support the relationships between them. Moreover, it is one of the most cited and most widely applied IS success models. Although factors such as negative citations and publication availability can compromise citations' reliability, one can still use them as an objective measure to determine a publication's usefulness (Culnan, 1986). As a result, we adopted this theoretical model to conduct a meta-analytic examination of DLP success.

In 2003, DeLone and Mclean refined their original model, which resulted in the addition of intention to use and service quality as additional success dimensions to the model. They also combined the two dimensions - organizational impact and individual impact into a single measure called net benefits. Thus, their updated IS success model included the following dimensions: system quality, information quality, service quality, intention to use/use, user satisfaction, and net benefits (see Table 1).

We propose that the updated IS success model can be adopted to better understand DLP success as the seven success dimensions align with the DLP context. The collective functionality, convenience, and reliability of complex technologies embedded in DLPs and the quality of service provided by the platform developers may influence the current and future use of these platforms. These issues are also expected to influence user satisfaction with these platforms. As learning depends on information, we can expect the quality of the information and knowledge that DLPs deliver to influence whether users use and feel satisfied with these platforms. We can also project that learners' use of DLPs, their perceptions of user satisfaction, and their intention to use DLPs would also be crucial dimensions of DLP success and that one would need to examine the relationships between these dimensions to develop a comprehensive understanding of DLP success. The net benefits that users gain from these platforms would also play a significant role in assessing DLP success. Based on these observations and guided by prior meta-analyses and theoretical reviews of

the updated IS success model (see Petter & McLean, 2009; Petter et al., 2008; Sabherwal et al., 2006), we hypothesize and test baseline relationships for DLP success (see Table 2).

Table 1. Dimensions of DLP Success

Dimension	Conceptual definition	Operationalization	Supporting literature
System quality	Desirable performance of IT-capabilities embedded in DLPs.	Measured in terms of system functionality, convenience, ease of use, reliability, adaptability, availability, response time, and usability.	Petter & McLean (2009), Sabherwal, Jeyaraj, & Chowa, (2006), DeLone & McLean (2003)
Information quality	Desirable characteristics of information generated by DLPs.	Measured as ease of understanding, personalization, relevance, accuracy, and timeliness of information.	Petter & McLean (2009), Rai, Lang, & Welker (2002), DeLone & McLean (2003)
Service quality	Quality of service and support received for DLPs from the IS department.	Measured as assurance, empathy, responsiveness, and service reliability.	DeLone & McLean (1992), Petter & McLean (2009), DeLone & McLean (2003)
Use/intention to use	Expected consumption of DLPs or of their future output.	Measured as nature of use, number of site visits, and navigation patterns.	Rai et al. (2002), Sabherwal et al. (2006), DeLone & McLean (2003)
User satisfaction	User's level of satisfaction with DLPs.	Measured as repeat use and sharing positive reviews of systems.	Doll & Torkzadeh (1998), Sabherwal et al. (2006), DeLone & McLean (2003)
Net benefits	DLPs' contribution to individual, group, or organizational success.	Measured as time savings, reduced costs of information search, and incremental additional sales.	Petter & McLean (2009), Petter, DeLone, & McLean (2008), DeLone & McLean (2003)

Table 2. Baseline Hypotheses (Petter & McLean, 2009)

Hypothesis	Hypothesis description	Inconsistencies in prior findings
H1	DLPs' system quality is significantly and positively related to intention to use.	-
H2	DLPs' system quality is significantly and positively related to their use.	-
H3	DLPs' system quality is significantly and positively related to user satisfaction.	Yes
H4	DLPs' information quality is significantly and positively related to intention to use.	-
H5	DLPs' information quality is significantly and positively related to their use.	-
H6	DLPs' information quality is significantly and positively related to user satisfaction.	Yes
H7	DLPs' service quality is significantly and positively related to intention to use.	Yes
H8	DLPs' service quality is significantly and positively related to use.	-
H9	DLPs' service quality is significantly and positively related to user satisfaction.	Yes
H10	DLP use is significantly and positively related to user satisfaction.	Yes
H11	User satisfaction with DLPs is significantly and positively related to intention to use.	Yes
H12	DLP use is significantly and positively related to their net benefits.	Yes
H13	User satisfaction with DLPs is significantly and positively related to their net benefits.	Yes
H14	Net benefits from DLPs is significantly and positively related to intention to use.	-

3 Moderating Effects

While selecting the moderators for this study, we followed a two-pronged process. First, we identified key contextual exigencies examined by prior research in relevant areas (e.g., DLP, e-learning, online learning research). Second, we relied on the theoretical recommendations from prior studies on IS success. We reviewed the relevant literature and found that researchers have extensively studied two user groups: 1) student learners and 2) organizational learners. Scholars have suggested the need to examine factors that shape IS success for students versus employees (Petter et al., 2008; Seddon, 1997). Prior theory also suggests that, given the different motivations and learning styles of higher education learners and organizational learners, the two user groups may value different DLP success dimensions (Tiwana & Ramesh, 2001; Foegl & Nehmad, 2009). In a meta-analysis of the technology adoption literature, King and He (2006) also reported that user context has a key moderating influence on various issues that govern system adoption, and recommended that one cannot generalize findings specific to student users to non-student users. Furthermore, in a meta-analysis of the system success literature, Petter and McLean (2009) observed that user population had strong contingency effects on various IS success dimensions. Guided by this evidence from prior literature, we propose that DLP user context (i.e., higher-education users versus organizational users) would moderate DLP success.

In reviewing the prior literature, we also found that researchers have conducted most studies on DLP and related technologies in a single cultural context (Gan & Balakrishnan, 2018; Kurt, 2019; Rana & Dwivedi, 2018). Theoretical evidence from the IS success literature suggests that different cultural schema may influence DLP success differently, yet prior studies have not examined these effects. Rai et al. (2009) observed that key contingencies embedded in different cultures create a unique schema that guides how each culture constructs the meaning of an information system. The unique norms and values embedded in this schema also shape the value that each culture places on different IS success dimensions. Several studies have reported that cultural nuances play a vital role in most if not all IT outcomes such that the factors that shape users' intentions, attitudes, adoption, and usage behaviors differ across cultures (Hossain & Quaddus, 2012; Sarkar, Chauhan, & Khare, 2020; Schepers & Wetzels, 2007; Zhang, Zhu, & Liu, 2012). The culture-specific findings of prior studies make it difficult to develop a common understanding of DLP success across different cultures. We fill this research gap by examining cultural context as the second moderating condition for DLP success.

Although we examine the moderating role of user and cultural context, one could examine other possible contingencies that influence DLP success. For example, mandatory versus voluntary use of DLPs could be a possible moderator (Petter & McLean, 2009; Sabherwal et al., 2006). The degree to which DLPs embed various IT capabilities such as gamification could also moderate DLP success. Previous studies have identified gamification as a popular method to improve learning outcomes, and it would be interesting to see how different levels of gamification in DLPs affected their success (Kankanhalli, Taher, Cavusoglu, & Kim, 2012; Hanus & Fox, 2015).

3.1 User Context

Scholars have highlighted a growing awareness of how different learners learn and have suggested that a "one-size-fits-all" approach to designing DLPs may run contrary to the core objective of these platforms to provide a flexible, personable, and contextualized learning experience (Tiwana & Ramesh, 2001). DLPs also offer contextualized peer-to-peer learning mechanisms (Tiwana & Ramesh, 2001), and higher education learners may use these mechanisms differently from organizational learners. For example, given higher levels of relational trust among higher education learners, they may use these peer-to-peer mechanisms more compared to organizational learners, who typically have lower levels of relational capital (Fogel & Nehmad, 2009). Researchers have also observed that the characteristics specific to a user context could differentially impact IS success (Hwang, Windsor, & Pryor, 2000; Sabherwal et al., 2006), and findings unique to one context may not generalize to other user contexts. For example, compared to higher education learners, organizational learners may have different motives for using DLPs, such as staying current with their job demands or looking for a highly specific skillset (Thompson, 2011).

Previous meta-analytic studies in technology acceptance have also reported contingency effects of user context (Chauhan & Jaiswal, 2017; King & He, 2006; Šumak, HeričKo, & Pušnik, 2011). King and He (2006) reported that contingencies embedded in different user contexts influence technology acceptance behaviors differently. Šumak et al. (2011) also found that the nature of relationships between various constructs related to e-learning acceptance vary across student learners and organizational learners.

Similarly, Peterson (2001) demonstrated that "effect sizes derived from college student subjects frequently differed from those derived from non-student subjects both directionally and in magnitude" (p. 450). These observations suggest that success patterns may differ between higher education learners and organizational learners.

Prior studies have also observed differing relationships among DLP success dimensions for higher education learners and organizational learners. For example, in an organizational context, several scholars have observed that system quality significantly affects user satisfaction (Chang, Liu, & Hwang, 2011; Chen & Kao, 2012; Yeung & Jordan, 2006), whereas other scholars found the same relationship to be insignificant for higher education learners (Balaban, Mu, & Divjak, 2013; Wang & Lai, 2014; Yakubu & Dasuki, 2018). User context possibly moderates this relationship such that system quality affects user satisfaction for organizational users but not for higher education users. Similarly, prior DLP studies in organizational context have found that both information quality and service quality significantly influence user satisfaction (Chang et al., 2011; Chen & Kao, 2012; Chuo et al., 2015; Yeung & Jordan, 2006). On the other hand, empirical studies that researchers conducted in higher education settings have confirmed that information quality and service quality do not influence user satisfaction (Chiu et al., 2007; Chiu, Chao, Kao, Pu, & Huang, 2016; Yakubu & Dasuki, 2018; Wang & Lai, 2014). These inconsistencies also hint that user context possibly moderates the influence that information and service quality have on DLP usage indices.

Researchers have also reported divided findings regarding usage indices for higher education and organizational learners. For example, Au, Ngai, and Cheng (2002) observed that user satisfaction varied among different user contexts even though systems performed at a similar level across those contexts. A considerable body of literature on organizational learners has also found significant relationships between user satisfaction, intention to use, and use of e-learning systems (Chang et al., 2011; Chen & Kao, 2002; Cheng, 2014; Ramayah, Ahmad, & Hong, 2012). On the other hand, another group of studies on higher education learners has observed non-significant relationships between these usage indices (Chiu et al., 2016; Yakubu & Dasuki, 2018). Finally, researchers have also found divided findings about the influence that user satisfaction has on DLPs' net benefits for higher education learners versus organizational learners (Chang et al., 2011). While one group of studies suggests that neither system use nor user satisfaction influences net benefit perceptions (Marjanovic, Delić, & Lalic, 2016; Ramayah, Ahmad, & Hong, 2012), other studies suggest that use and user satisfaction strongly influence net benefit perceptions (Aldholay, Abdullah, Isaac, & Mutahar, 2019; Kurt, 2019; Martins et al., 2019). These conflicting findings also suggest that the two user contexts have possible contingency effects on how DLP use and user satisfaction shape the net benefits provided by these platforms.

Overall, we propose that DLP success (as constructed by the IS success model) would differ for higher education learners versus organizational learners. In other words, we propose that user context moderates various relationships that define DLP success (see Table 3).

Table 3. Hypotheses for User Context Moderation Effects

Hypothesis	Hypothesis description
H15a	User context moderates the relationship between DLP system quality and intention to use.
H15b	User context moderates the relationship between DLP system quality and use.
H15c	User context moderates the relationship between DLP system quality and user satisfaction.
H15d	User context moderates the relationship between DLP information quality and intention to use.
H15e	User context moderates the relationship between DLP information quality and use.
H15f	User context moderates the relationship between DLP information quality and user satisfaction.
H15g	User context moderates the relationship between DLP service quality and intention to use.
H15h	User context moderates the relationship between DLP service quality and use.
H15i	User context moderates the relationship between DLP service quality and user satisfaction.
H15j	User context moderates the relationship between DLP use and user satisfaction.
H15k	User context moderates the relationship between DLP user satisfaction and intention to use.
H15l	User context moderates the relationship between DLP use and net benefits.
H15m	User context moderates the relationship between DLP user satisfaction and net benefits.
H15n	User context moderates the relationship between DLP net benefits and intention to use.

3.2   Cultural Context

Prior literature suggests that cultural differences could impact IT outcomes (Sarkar et al., 2020; Schepers & Wetzels, 2007). For example, Zhang et al. (2012) observed different technology adoption behaviors across Western and Eastern cultures and suggested that one should stress different factors in different cultures to convince users to adopt the same technology. Scholars have also proposed that differences in IT outcomes across cultures probably emerge from differences in core cultural values (Singh et al., 2006). Hofstede's (1984) individualism/collectivism cultural dimensions play a key role in this context. People in Western cultures are typically characterized by individualism, whereas people in Eastern cultures are typically more collectivist (Hofstede, 1984). Individualism upholds the cultural value of achieving personal interests, and Western cultures may value DLPs that offer more personalized learning preferences and deliver learning experiences aligned with one's unique preferences (Rai et al., 2009). On the other hand, collectivism favors group or social goals over individual interests (Rai et al., 2009). As a result, Eastern cultures may prefer DLP functionalities that enhance collaborative learning experiences. Studies on e-learning systems have observed that culture has a key influence on the implementation of these systems and that the individualism/collectivism cultural dimensions influence e-learning success across Eastern and Western cultures (Ali, Uppal, & Gulliver, 2018).

In addition to the individualism/collectivism cultural dimension, cultural variations in IS accessibility could also explain the divergence in prior findings. Eastern and Western cultures vary in IS accessibility due to varying socio-economic conditions (Carter & Weerakkody, 2008). This variance may induce differences in individuals' IS-related knowledge, capability, and skillfulness across different cultures (Hossain & Quaddus, 2012). Accessibility may also create different cultural expectations from IS. Western cultures, with their access to a wide variety of DLPs may have high quality expectations from these systems, whereas Eastern cultures may have more moderate quality expectations. Differences in how DLPs meet or do not meet these expectations may induce significant variance in use behaviors, satisfaction perceptions, and future intention to use these platforms.

Researchers have also reported divergent findings about DLP success across the two cultural settings. Studies in Western context have reported significant relationships between system quality and user satisfaction (Kurt, 2019; Rana & Dwivedi, 2018). On the other hand, researchers have reported non-significant results for the same relationships in Eastern context (Chuo et al., 2015; Wang et al., 2014). Along the same lines, Yakubu and Dasuki (2018) found information quality to be non-significant for shaping user satisfaction in Eastern cultures, but Rana and Dwivedi (2019) reported opposite effects for users from Western cultures. Results for service quality also show divergent patterns between the two cultures. Studies conducted in Western contexts have reported significant positive relationships between DLP service quality and usage indices (Doleck, Lajoie, & Bazelais, 2019; Martins et al., 2019), whereas studies conducted in Eastern contexts have reported both non-significant and negative effects between DLP service quality and user satisfaction (Wang & Lai, 2014; Yeung & Jordan, 2006). These inconsistencies suggest that cultural context moderates the relationship between the three quality dimensions (i.e., system quality, information quality, and service quality) and DLP usage indices.

Prior findings regarding the influence of various DLP usage indices on net benefits also diverge across the two cultural contexts. Scholars have largely observed a positive relationship between user satisfaction and benefit perceptions in Western cultures (Kurt, 2019; Martins et al., 2019). On the other hand, scholars have found that in Eastern cultures, user satisfaction with DLP systems may not significantly shape their net benefit perceptions (Ramayah et al., 2012). Similarly, scholars have found that users in Western cultures typically exhibit a stronger intention to use a DLP system if they are more satisfied with the system (Daughan & Akkoyunlu, 2016), but did not find evidence to support this relationship in Eastern cultures (Chiu et al., 2016; Yakubu & Dasuki, 2018). Studies have also reported that while DLP use shapes net benefit perceptions more in collectivist (Eastern) cultures, user satisfaction plays a stronger role in shaping net benefit perceptions in Western cultures (Aparicio et al., 2016). Overall, in view of the theoretical and empirical evidence presented above, we propose that contingencies embedded in these cultures moderate baseline relationships that define DLP success. We list the moderation hypotheses in Table 4.

Table 4. Hypotheses for Moderation Effects of Cultural Context

Hypothesis	Hypothesis description
H16a	Cultural context moderates the relationship between DLP system quality and intention to use.
H16b	Cultural context moderates the relationship between DLP system quality and use.
H16c	Cultural context moderates the relationship between DLP system quality and user satisfaction.
H16d	Cultural context moderates the relationship between DLP information quality and intention to use.
H16e	Cultural context moderates the relationship between DLP information quality and use.
H16f	Cultural context moderates the relationship between DLP information quality and user satisfaction.
H16g	Cultural context moderates the relationship between DLP service quality and intention to use.
H16h	Cultural context moderates the relationship between DLP service quality and use.
H16i	Cultural context moderates the relationship between DLP service quality and user satisfaction.
H16j	Cultural context moderates the relationship between DLP use and user satisfaction.
H16k	Cultural context moderates the relationship between DLP use and net benefits.
H16l	Cultural context moderates the relationship between DLP user satisfaction and intention to use.
H16m	Cultural context moderates the relationship between DLP user satisfaction and net benefits.
H16n	Cultural context moderates the relationship between DLP net benefits and intention to use.

4   Research Method

4.1   Data Collection

To collect data, we followed the steps that Figure 1 lists. First, we conducted a comprehensive search in various electronic databases such as EBSCO, ScienceDirect, Taylor & Francis, Emerald, SAGE, Scopus, Google Scholar, and Web of Science. We collected all papers published from 2006 to 2019 from these databases by using certain search terms. Table 5 lists the relevant search terms with their key classification. We joined the search terms for both classifications with the Boolean "AND" operator. Thus, we used every possible permutation of search terms from both classifications, which resulted in 135 research papers.
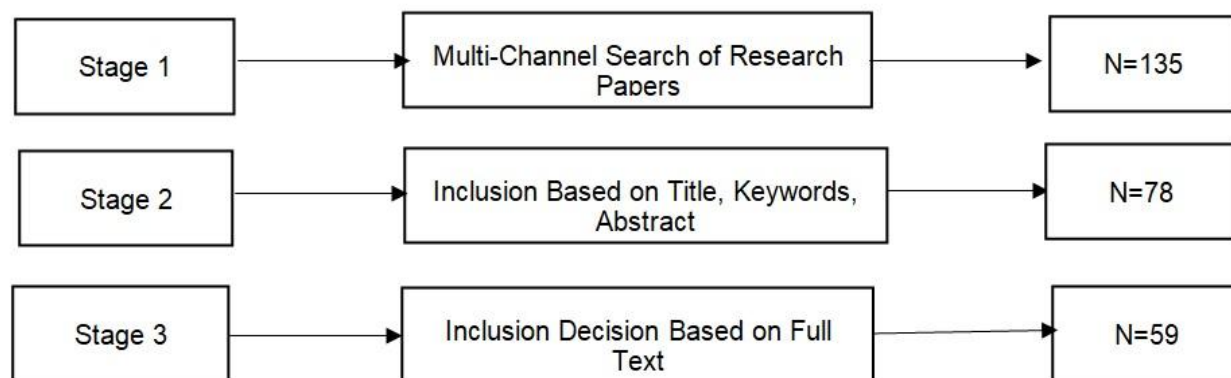
Figure 1. Three-stage Data-collection Process

Second, three researchers independently read each paper's title, keywords, and abstract to shortlist the relevant studies. As a result, we excluded papers that did not examine DLP success using the IS success model. At this stage, we also eliminated duplicate papers and ensured that we included only peer-reviewed journal papers. Peer-reviewed journal papers go through an evaluation process that ensures a certain level of rigor (David & Han, 2004; Light & Pillemer, 1984). In other words, we excluded notes, press articles, book chapters, books, short surveys, editorials, reviews, and conference papers. Two researchers jointly eliminated the irrelevant research papers. Later, the third researcher read the titles, keywords, and abstracts of the eliminated research papers to make sure that we did not eliminate any relevant research paper. After independent shortlisting, we matched our final outcomes. The fourth

researcher helped achieve consensus in situations involving a disagreement. After this process, our sample was reduced to 78 research papers.

Table 5. Search Terms used for the Literature Review

Type	Classification	Search terms
1	Learning	Digital learning platform, learning, education, e-learning, electronic learning, online learning, learner, learning management system,
2	Success	DeLone & McLean, D&M, DeLone and McLean, information systems success, information system success, IS success model

In the final stage, three researchers independently read the full text of every paper and shortlisted the relevant ones. We followed the following criteria for including papers:

- Does the paper mention a clear research objective?
- Does the paper define and operationalize the IS success model dimensions according to Table 1?
- Does the research paper quantitatively examine at least one relationship between two constructs of the IS success model?
- Does the research paper report the correlation coefficient or another statistic (e.g., F-ratio and student's t) that one could convert to the correlation coefficient of the examined relationships?

We matched our outcomes to identify any discrepancy. Again, the fourth researcher helped achieve consensus in instances involving a disagreement. At the end of the third stage, the final sample for our meta-analysis included 59 research papers. These papers are listed in Appendix A.

Figure 2 depicts the year-wise distribution of research papers. Although the number of published research papers that examined various dimensions of DLP success varied across years, the trend clearly indicates an overall increase in the academic interest in this key issue. This body of research offers rich findings to review, consolidate, and reconcile. Researchers can use several qualitative and quantitative methods to review existing literature, such as narrative review, descriptive review, vote counting, meta-analysis, and so on (King & He, 2005). For our study, we used the meta-analysis technique, which is considered a rigorous alternative to qualitative literature reviews (Borenstein, Hedges, & Rothstein, 2007; King & He, 2006). We decided to perform a meta-analysis for our study for three main reasons. First, meta-analysis presents an evidence-based method to synthesize the existing findings (Petrie, Bulman, & Osborn, 2003). Second, meta-analysis helps researchers examine probable moderating effects that explain heterogeneity in primary studies (Frese, Rousseau, & Wiklund, 2014). Third, meta-analysis offers higher statistical power by integrating the quantitative results of multiple primary studies' and eluding the statistical shortcomings of a single study (Schmidt & Hunter, 2004).
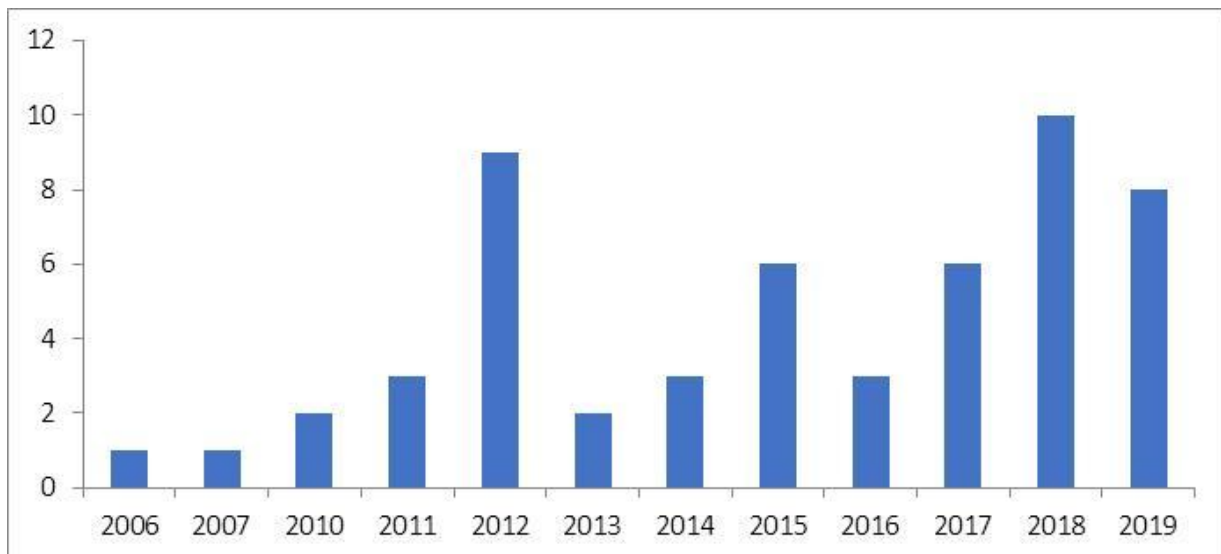

Figure 2. Year-wise Distribution of Research Papers

4.2 Coding Procedure

We documented information such as paper title, authors, country in which researchers conducted their research, publication year, source, correlation coefficients, and sample size for every research paper. If a research paper had multiple substudies, we treated each one as a distinct study. Therefore, the final dataset included 61 studies. Furthermore, we classified each study based on its cultural context (Western or Eastern) and user context (higher education learners or organizational learners) to conduct moderator analysis. Based on the criteria that previous meta-analytic studies have used (e.g. Anderson et al., 2010; Schepers & Wetzels, 2007; Zhang et al., 2012), we categorized studies that researchers conducted in Europe, United Kingdom, North America, Australia, and New Zealand into the Western cultural context. We classified the remaining studies into the Eastern cultural context. Additional details about the studies are provided in Appendix B. Reliability indices for each IS success measure (Cronbach's alpha coefficient) were recorded; they all exceeded the recommended value (i.e., 0.7).

4.3 Statistical Analysis

In this study, we conducted a meta-analysis to examine the joint effect of multiple research findings. Meta-analysis is a suitable method to achieve this objective. Meta-analysis can be conducted using either a fixed-effect model or a random-effect model. The fixed-effect model assumes that a single true effect size commonly exists in every study, while the random effect model assumes that true effect size varies from one study to another (Borenstein et al., 2007). A fixed effect model constitutes the appropriate choice when one examines studies conducted in a controlled environment in a comparable way. However, we chose a random effect model for our meta-analysis since it assumes the presence of samples from populations with different effect sizes (Borenstein et al., 2007).

We used the correlation coefficient as the effect size metric[2]. Effect size estimates the magnitude of a phenomenon that exists in a population (Cohen, West, & Aiken, 2014). Higher effect sizes signify that a phenomenon exists to a greater extent. As previous scholars have suggested, we followed five steps to conduct our meta-analysis (Hedges & Vevea, 1998; Lipsey & Wilson, 2001).

In the first step, we conducted a Fisher transformation of the correlation coefficients as follows:

$$\text{Fisher transformation } (T_i) = 0.5 * \log\frac{1+r_i}{1-r_i}, \tag{1}$$

where r_i = correlation coefficient for i^{th} study.

In the second step, we assessed the statistical significance level of the overall effect size via the p-value associated with it.

In the third step, for subgroup analyses, we used the Q-statistic to evaluate homogeneity between the findings from different sub-groups. Q-statistics is the weighted variance of the effect size metric. It describes the variability in the effect size estimate due to the heterogeneity in the sample rather than sampling error (Hong, Xu, Wang, & Fan, 2017). We calculated the Q-statistic as:

$$Q = \sum_{i=1}^{n} W_i * (T_i - \overline{T})^2, \tag{2}$$

where Q = heterogeneity statistic, W_i = sample size of ith study, and $\overline{T} = \sum(W_i * T_i)/\sum W_i$.

The overall effect size was calculated as:

$$T \text{ (overall)} = \sum_{i=1}^{n} W'_i * T_i, \tag{3}$$

where $1/W'_i = 1/W_i + \tau^2$, $\tau^2 = \text{Max } [0, (Q\text{-df})/C]$, $C = \sum W_i - \frac{\sum W_i^2}{\sum W_i}$, df = degrees of freedom, and overall effect size $(\bar{r}) = \frac{e^{2T(overall)}-1}{e^{2T(overall)}+1}$.

In the fourth step, we checked the significance level of the combined effect size via the p-value associated with it. Given the existing criticisms that p-value reporting has received (Mertens & Recker, 2020), we also

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[2] Correlations table is available from the authors.

calculated 95 percent confidence intervals for the meta-analytic effect sizes. The confidence intervals not including zero suggest significant relationships (Hwang, 1996).

In the fifth step, we tested for publication bias by determining the fail-safe N value for every relationship, since such bias can affect quantitative review studies. This bias arises when journals have a tendency to publish research papers that include statistically significant results. Table 6 shows that every fail-safe N value exceeded the suggested value 5N+10 where N represents the total count of studies for every relationship (Rosenthal, 1991). As such, publication bias did not likely pose an issue in this study.

5   Findings

We summarize our meta-analysis results for the baseline hypotheses in Table 6. Results show that relationships between all success dimensions were significant for DLPs except for the relationship between DLP service quality and use. Thus, we found support for all hypotheses except H8.

Table 6. Effect Sizes for Baseline Relationships

Relationship (hypothesis)	Study count	Sample size	Combined effect size	p(effect size)	95% upper	95% lower	Q-value (Homogeneity test)	p (Q-value)	Fail-safe N
DLP system quality → intention to use (H1)	28	9689	0.450	0.000	0.560	0.326	1511.925	0.000	5044.408
DLP system quality → use (H2)	22	6954	0.324	0.000	0.444	0.192	750.664	0.000	1062.885
DLP system quality → user satisfaction (H3)	46	14187	0.540	0.000	0.609	0.463	1658.918	0.000	11850.258
DLP information quality → intention to use (H4)	30	10281	0.490	0.000	0.590	0.374	1568.537	0.000	6402.764
DLP information quality → use (H5)	21	6675	0.301	0.000	0.444	0.145	1077.148	0.000	915.187
DLP information quality → user satisfaction (H6)	46	14220	0.541	0.000	0.610	0.463	1876.976	0.000	12053.334
DLP service quality → intention to use (H7)	20	7399	0.408	0.000	0.567	0.220	1664.037	0.000	1488.872
DLP service quality → use (H8)	14	4943	0.179	0.056	0.384	-0.043	904.860	0.000	325.600
DLP service quality → user satisfaction (H9)	31	10042	0.477	0.000	0.568	0.375	1305.444	0.000	4416.841
DLP use → user satisfaction (H10)	25	8299	0.500	0.000	0.564	0.420	421.891	0.000	4422.832
DLP user satisfaction → intention to use (H11)	23	9264	0.607	0.000	0.726	0.453	2224.067	0.000	3781.553
DLP use → net benefits (H12)	20	5907	0.527	0.000	0.618	0.422	523.348	0.000	3215.392
DLP user satisfaction → net benefits (H13)	31	10477	0.647	0.000	0.717	0.564	1575.761	0.000	8605.949
DLP net benefits → intention to use (H14)	13	5090	0.561	0.000	0.673	0.423	424.823	0.000	1115.158

Meta-analytic methods allow one to assess the strength of a relationship between two constructs (Petter & Mclean, 2009). According to Cohen et al. (2014), 0.5 constitutes a strong effect size, 0.3 a moderate effect size, and 0.1 a weak effect size. In our analysis, all the significant relationships had either moderate or strong effect sizes. Specifically, we found that the quality of the platform itself (system quality) and the information output (information quality) strongly shaped DLP user satisfaction. DLPs combine multiple innovative technologies, and our results suggest that the convenience, reliability, and ease of use of these technologies play a vital role in eliciting user satisfaction. Additionally, our results suggest that user satisfaction strongly depends on the completeness, usability, and appropriateness of the information delivered by a DLP. Interestingly, we found that system and information quality dimensions only moderately affected the actual use of digital platforms, which suggests that we need to look for stronger determinants of DLP use outside the IS success model. DLP use had a strong influence on user

satisfaction, and user satisfaction seemed to have a more compelling influence on net benefits compared to use.

Another interesting finding is that service quality plays a moderate role in shaping both user satisfaction and intention to use for DLPs. These results differ from previous meta-analyses of general IS success that either could not examine service quality's role or found insignificant results (Petter & McLean, 2009). Given that DLPs offer a complex bundle of functionalities, it makes sense that the support and responsiveness offered by platform developers or IT departments would markedly affect a platform's likeability and future use. On the other hand, the absence of a significant relationship between service quality and DLP use suggests that use depends more on the system and information quality dimensions than on service quality.

Compared to previous meta-analysis, we also found different results for DLP use shaping user satisfaction and satisfaction shaping both net benefits and intention to use (Petter & McLean, 2009). These results suggest that, compared to other systems, DLP use plays a key role in shaping user satisfaction for these systems.

We found significant Q-values (heterogeneity test) for all relationships, which indicate the presence of high heterogeneity across studies. These values suggest that the variability in effect sizes exceeds what could have resulted from sampling error, which provides further support for our choice to use a random effects model (Hong et al., 2017).

5.1   Moderating Effects of User Context

In Table 7, we summarize the findings of the moderation analysis of user-context. Analysis shows that Q-statistic value was significant for eight out of twelve relationships, suggesting that user-context moderates these eight relationships (we could not examine some relationships due to insufficient data[3]). We did not examine the relationship between service quality and use since its main effects lacked significance. Four relationships did not differ across the two user-contexts: 1) DLP system quality → intention to use (H15a), 2) DLP system quality → user satisfaction (H15c), 3) DLP information quality → user satisfaction (H15f), and 4) DLP service quality → user satisfaction (H15i) (see Table 7). These results suggest that both higher education learners and organizational learners consider DLP system quality as an important criterion while making their intention to use decision. Results also suggest that the three quality dimensions of DLPs are key to shaping user satisfaction perceptions of both user groups.

We found that user context moderates the influence that both DLP system quality and DLP information quality have on use. These relationships were significant for higher education learners but not for organizational learners, which suggests that a DLP's quality and the quality of its information output both influence its use among higher education learners but not among organizational learners. Our results suggest that other factors could influence DLP use among organizational learners, such as organizational policies (Nisar, 2002). For example, some organizations mandate the use DLPs. Since organizational learners need to use these functionalities in their job-related training, system or information quality may not influence their use behavior. This implication aligns with DeLone and McLean's (2003) proposition that DLP use constitutes a complicated, multi-dimensional variable that could vary significantly across different contexts.

Results also suggest that the influence that information quality and service quality had on intention to use differed among the two user contexts. Specifically, we found that DLP information quality had a stronger influence on intention to use for organizational learners, which suggests that organizational learners value the timeliness, completeness, and applicability of learning delivered by a DLP while making their intention to use decision. On the other hand, we found that service quality only affected intention to use for higher education learners. These results make sense as organizational learners' intention to use depends more on what specifically helps them improve their performance (i.e., the quality of information that DLPs offer) (Cheng, 2011). On the other hand, higher education learners are typically more interested in exploring all learning functionalities DLPs offer. This necessitates positive and helpful interactions with the platform's service providers (Shin, 2003). As a result, intention to use DLPs for higher education learners is contingent more on a DLP's service quality.

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[3] Following Kirca, Jayachandran, and Bearden's (2005) recommendations, we conducted a meta-analysis for relationships that had been examined at least three times in our sample of studies.

Table 7. User Context as a Moderator of DLP Success

Relationship (Hypothesis)	User context	Study count	Sample size	Combined effect size	p(effect size)	95% upper	95% lower	Q-value of two groups (homogeneity test)	p(Q-value of two groups)
DLP system quality → intention to use (H15a)	HEL	21	7037	0.427	0.000	0.602	0.213	1.438	0.231
	OL	4	1626	0.460	0.019	0.723	0.081		
DLP system quality → use (H15b)	HEL	18	6085	0.305	0.003	0.482	0.105	5.756	0.017
	OL	4	869	0.392	0.123	0.736	-0.112		
DLP system quality → user satisfaction (H15c)	HEL	37	11642	0.537	0.000	0.654	0.395	0.002	0.965
	OL	7	1813	0.538	0.017	0.799	0.108		
DLP information quality → intention to use (H15d)	HEL	22	7435	0.456	0.000	0.628	0.242	12.375	0.000
	OL	5	1820	0.548	0.000	0.739	0.277		
DLP information quality → use (H15e)	HEL	18	6085	0.281	0.012	0.473	0.063	9.51	0.002
	OL	3	590	0.414	0.166	0.787	-0.181		
DLP information quality → user satisfaction (H15f)	HEL	37	11760	0.535	0.000	0.657	0.384	0.122	0.714
	OL	7	1728	0.544	0.001	0.752	0.237		
DLP service quality → intention to use (H15g)	HEL	14	4907	0.406	0.015	0.651	0.084	19.083	0.000
	OL	4	1626	0.281	0.150	0.593	-0.104		
DLP service quality → user satisfaction (H15i)	HEL	26	8314	0.475	0.000	0.618	0.302	0.082	0.780
	OL	4	1156	0.484	0.158	0.851	-0.202		
DLP use → user satisfaction (H15j)	HEL	21	7456	0.509	0.000	0.645	0.341	11.834	0.001
	OL	4	843	0.384	0.169	0.754	-0.171		
DLP user satisfaction → intention to use (H15k)	HEL	18	7752	0.615	0.000	0.798	0.330	10.897	0.001
	OL	3	780	0.491	0.001	0.690	0.223		
DLP use → net benefits (H15l)	HEL	16	5064	0.558	0.000	0.726	0.326	31.568	0.000
	OL	4	843	0.349	0.147	0.695	-0.127		
DLP user satisfaction → net benefits (H15m)	HEL	23	8500	0.663	0.000	0.809	0.438	7.481	0.007
	OL	6	1245	0.580	0.003	0.803	0.216		

Note: HEL = higher education learners, OL = organizational learners.

Our findings also suggest that user context moderates the relationship that DLP use has with both user satisfaction and net benefits. Interestingly, DLP use had a significant influence on shaping user satisfaction and net benefits for higher education learners but not for organizational learners. Again, our findings suggest that a possible mandatory use policy for employees could prevent DLP use from influencing how employees perceive satisfaction and net benefits. Prior findings that IS use may not influence user satisfaction in a mandatory use context support this implication (Seddon & Kiew, 1996).

Finally, we found that user context also moderated the influence that DLP user satisfaction had on both the intention to use DLPs and the benefits derived from them. Both relationships were more compelling for higher education users. Our findings suggest that, if they have higher perceived satisfaction, student learners have a higher inclination to use DLPs in the future compared to organizational learners. Our findings also show that students would typically more strongly perceive that they derive benefits from DLPs if they have higher satisfaction levels. These results indicate the alignment, or misalignment, between DLPs' learning focus and the respective needs of the two user groups. DLPs strongly serve students' learning needs, which makes students more vested in all aspects of DLP success (Cakir, 2013; Klobas & McGill, 2010). In contrast, organizational learners' performance needs may not completely align with DLPs' core learning objective and, which reduces their overall investment in these systems (Seow, Hughes, Waight, & Stewart, 2005).

5.2   Moderating Effects of Cultural Context

In Table 8, we summarize the findings for the moderation effects of cultural context. We could examine contingency effects of cultural context for nine relationships (as with user context, we could not examine some relationships due to insufficient data). We did not examine the relationship between service quality and use since it lacked significance in the baseline analysis. We found an insignificant Q-value for the DLP system quality → user satisfaction relationship, which indicates that DLP system quality has a strong influence on user satisfaction across both Eastern and Western cultures. However, we found significant Q- values for the remaining observed relationships.

Our results suggest that, given their higher effect size, both DLP system quality and DLP information quality have a more compelling influence on DLP use in Western cultures compared to Eastern cultures (see Table 8). Our results suggest that the use decision in Eastern cultures may not depend strongly on DLP system quality or DLP information quality. As for why, one reason could be the typical dearth of technological resources in some Eastern cultures compared to Western cultures, which makes learners in Eastern cultures less sensitive to the quality of platforms available to them (Chen, Jubilado, Capistrano, & Yen, 2015; Venkatesh et al., 2014).

Similarly, we found that both DLP information quality and service quality had a more compelling influence on user satisfaction among Western cultures. These findings suggest that DLP information and service quality more strongly affect how users in Western cultures perceive DLPs to satisfactorily meet their learning and training needs. As for why, easy availability of multiple DLPs in most Western cultures may possibly cause users in these cultures to expect higher information and service quality compared to users in Eastern cultures.

Finally, in Western cultures, users' satisfaction with DLPs had a stronger influence on their benefit perceptions. Also, in Western cultures, DLP use elicited moderate perceptions of user satisfaction and net benefits, whereas in Eastern cultures, DLP use led to strong perceptions of user satisfaction and net benefits. These results suggest that, in Western cultures, user satisfaction defines DLP benefits more strongly than actual DLP use does. However, in Eastern cultures, simple DLP use elicits users to strongly perceive both satisfaction and benefits derived from these platforms. These results could again be attributed to the relative lack of technological ubiquity in Eastern cultures (Venkatesh et al., 2014).

Table 8. Cultural Context as a Moderator of DLP Success

Relationship (Hypothesis)	Cultural context	Study count	Sample size	Combined effect size	p(effect size)	95% upper	95% lower	Q-value of two groups (homogeneity test)	p(Q-value of two groups)
DLP system quality → use (H16b)	EC	13	4582	0.239	0.027	0.430	0.028	67.618	0.000
	WC	9	2372	0.447	0.000	0.536	0.348		
DLP system quality → user satisfaction (H16c)	EC	36	11348	0.533	0.000	0.612	0.443	2.782	0.094
	WC	10	2839	0.568	0.000	0.715	0.371		
DLP information quality → use (H16e)	EC	13	4582	0.253	0.047	0.472	0.003	37.705	0.000
	WC	8	2093	0.415	0.000	0.524	0.292		
DLP information quality → user satisfaction (H16f)	EC	37	11660	0.526	0.000	0.604	0.437	11.186	0.001
	WC	9	2560	0.599	0.000	0.752	0.386		
DLP service quality → user satisfaction (H16i)	EC	26	8578	0.466	0.000	0.572	0.344	4.807	0.027
	WC	5	1464	0.528	0.002	0.742	0.218		
DLP use → user satisfaction (H16j)	EC	17	6065	0.535	0.000	0.610	0.450	21.218	0.000
	WC	8	2234	0.421	0.000	0.562	0.256		
DLP use → net benefits (H16k)	EC	13	3912	0.564	0.000	0.671	0.434	16.573	0.000
	WC	7	1995	0.452	0.003	0.667	0.168		
DLP user satisfaction → net benefits (H16m)	EC	24	8482	0.604	0.000	0.681	0.513	43.972	0.000
	WC	7	1995	0.769	0.000	0.886	0.559		
Note: EC = Eastern cultures, WC = Western cultures.									

6   Implications

We used meta-analytic procedures to report the synthesized results of multiple independent studies that examined DLP success as captured by the IS success model (DeLone & McLean, 2003). We observed significant variability in the path coefficients among the reviewed research studies, which supported our analysis of how two moderating conditions (user context and cultural context) influence DLP success. Our findings and resulting insights make unique contributions to theory and practice.

6.1   Implications for Research

With this study, we make several key theoretical contributions. First, by using rigorous meta-analytic procedures to examine DLP success, our study helps develop a more comprehensive and accurate understanding of DLP success. The study helps improve the accuracy of our understanding by reconciling inconsistencies in prior research findings. For example, prior research has reported conflicting findings about the influence that DLP quality dimensions have on user satisfaction. Specifically, some studies have proposed that system quality and information quality do not influence user satisfaction (Chuo et al., 2015; Yakubu & Dasuki, 2018), while other studies have suggested that these quality dimensions do influence user satisfaction (Alzahrani et al., 2019; Martins et al., 2019). Our results help reconcile these contradictions by highlighting contextual patterns. For example, we found that, whereas system quality and information quality affect user satisfaction strongly across all contexts (user and cultural), service quality strongly affects user satisfaction only in Western cultures. Service quality also plays a moderately important role in shaping user satisfaction for higher education learners and for users in Eastern cultures.

Scholars also disagree regarding the influence that DLP use and user satisfaction have on net benefits derived from these platforms. Again, our results show clear contextual patterns that help improve the accuracy of our understanding of DLP success. DLP use plays a more critical role in shaping net benefits in Eastern cultures, and comparatively, user satisfaction has a stronger influence on net benefits in Western cultures. Additionally, DLP use strongly affects net benefits only for higher education learners, and, although user satisfaction shapes benefit strongly for both user groups, the influence is more prominent for higher education learners. These patterns show the relative importance of user satisfaction and use as two key DLP success dimensions and provide more precise theoretical guidance to future studies.

Our findings also advance theory by reporting the moderating effects of user context and cultural context. Contingencies embedded in different user contexts motivate differing levels of systemic investment that higher education learners and organizational learners place in DLPs. Results also suggest that both DLP success criteria and the nature of their interrelationships vary across cultures. Future studies could examine if these variations in DLP success align with the individualism/collectivism theoretical framework (Hofstede, 1984; Rai et al., 2009). Specifically, researchers could examine if the individualistic orientation in Western cultures guides users to perceive DLPs as beneficial when they feel satisfied that the DLPs helped them achieve their unique learning goals. Scholars could also examine whether a strong sense of group belonging among collectivist cultures diminishes the influence that user satisfaction has on the net benefits that users perceive they derive from DLPs (Aparicio et al., 2016). Future studies could also examine the efficacy of different DLP success portfolios that emerge from our examination of user and cultural contexts. For example, future research could compare successful DLP implementations across the two user or cultural contexts.

Our findings also expand the boundaries of the IS success model by providing evidence of its effectiveness in capturing the success of emerging technologies such as DLPs. In addition, our findings about the influence that DLP service quality has on user satisfaction and intention to use, add to the IS success literature (Petter et al., 2008; Petter & McLean, 2009). Our findings highlight the importance of service quality construct, validating its inclusion as a key success dimension in the updated IS success model (DeLone & McLean, 2003).

Finally, previous studies have highlighted the complicated nature of system use construct (DeLone & McLean, 2003; Doll & Torkzadeh, 1998). Our results help define the boundaries of system use construct in IS success theory. For example, results of our cultural context moderation analysis show that the use construct has both the maturity and the flexibility to capture the moderating influence of various cultural nuances. Specifically, in Eastern cultures, DLP use depends less on the quality dimensions compared to

Western cultures. The results we obtained from our user context analysis also help define the theoretical limits of system use construct by suggesting that, in some conditions[4], intention to use may capture more variability across contexts and may better indicate success, compared to use. These contributions improve the overall efficacy of IS success model.

6.2   Implications for Practice

Our study has several implications for various DLP stakeholders (users, platform developers, content developers). These implications are especially relevant given the increasing relevance of DLPs during the COVID-19 pandemic. The results suggest that organizations can promote DLP use among higher education learners by improving platform (system) quality to help them achieve their learning goals. On the other hand, intention to use DLPs among organizational learners seems to be guided more by their performance goals. Our study also suggests that, compared to use, intention to use constitutes a better success metric for organizational learners. To create strong intention to use, organizations should improve DLP information quality by providing high-quality content that could help users achieve their performance goals. Our results suggest that doing so would also improve organizational learners' satisfaction levels, which in turn, would further fuel their intention to use DLPs. Organizations should also note that user satisfaction, and not mere use of DLPs, fosters users to perceive that they derive net benefits from these platforms. Thus, mandating DLP use may harm organizations' objective of using these platforms to develop talent and improve the overall quality of their human resources.

Our results from analyzing cultural context as a contingency condition also have useful implications for DLP developers. Our results suggest that users in Western cultures expect higher information and service quality given their increasingly widespread access to DLPs. In addition, given their more individualistic orientation, users in Western cultures have higher satisfaction levels only when they achieve their unique learning goals. We recommend that DLP developers embed IT functionalities such as AI and machine learning more in their platforms for Western cultures to learn about user-specific preferences and provide high-quality user-specific content. On the other hand, the more collectivist orientation of Eastern cultures may require platform developers to embed functionalities such as discussion forums, which enable collaborative learning experiences among users. Platform developers in Eastern cultures should also strive to foster actual DLP use to improve users' perceptions of satisfaction and net benefits derived from these platforms.

6.3   Limitations

Although we followed rigorous meta-analytic procedures, our study has some limitations that one should consider when interpreting the results. First, we examined only the moderating effects of user context and cultural context on DLP success. Future studies could examine other possible contingencies. For example, they could examine the moderating impact that voluntary use has on DLP success versus mandated DLP use in an institutional context. They could also examine the moderating effects of the level of IT capabilities (such as AI or gamification) embedded in DLPs. Second, we used various key search terms to extract research papers from popular online databases. However, we may have missed relevant research papers that additional search terms would have uncovered. Third, publication bias may have affected our results as journals often have a tendency to publish research that contains significant findings. However, fail-safe N values suggest that publication bias did not pose a major concern. Further, this study might also suffer from sampling bias as we examined only studies that included the necessary information to determine effect size. Given the statistical nature of meta-analytic procedures, the possibility of sampling bias towards quantitative studies that report effect sizes is inherent in meta-analytic procedures (King & He, 2005; Rosenthal, 1991). Finally, we could not test some relationships in our moderation analysis due to the unavailability of relevant literature related to these relationships. For example, we could not test the service quality → intention to use relationship for the user context, or the system quality → intention to use relationship for cultural context. As more research emerges in this area, researchers can study these relationships in the future.

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[4] Such as when organizational policy mandates that users use digital platforms.

7   Conclusions

In this paper, we report the results of a comprehensive examination conducted to better understand various issues that influence DLP success. To reconcile gaping inconsistencies in current findings on DLP success, we conducted rigorous meta-analyses of published studies between 2006 and 2019. We used the widely cited DeLone and McLean's (2003) updated IS success model as our theoretical foundation. Our results contribute not only to the DLP literature but also help improve the precision of IS success theory. In examining user context and cultural context as contingencies that affect DLP success, we help improve our understanding of DLP success. Future studies would benefit from the improved theoretical accuracy. Our results also provide useful implications for DLP users, platform developers, and DLP content creators.

Acknowledgements

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Appendix A: Studies in the Meta-analysis

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8   Appendix B: Information about Studies in the Meta-Analysis

Table B1. Information about Studies in the Meta-Analysis

No.	Authors	Year	Sample size	Country	Cultural context	User context
1	Yeung & Jordan (2006)	2006	212	Hong Kong	Eastern	OL
2	Chiu et al. (2007)	2007	289	Taiwan	Eastern	HEL
3	Adeyinka & Mutula (2010)	2010	381	Botswana	Eastern	HEL
4	Chen (2010)	2010	193	Taiwan	Eastern	OL
5	Tella (2011)	2011	503	Botswana	Eastern	HEL
6	Chang et al. (2011)	2011	208	Taiwan	Eastern	OL
7	Hsieh & Cho (2011)	2011	445	China	Eastern	HEL
8	Hsieh & Cho (2011)	2011	288	China	Eastern	HEL
9	Lin & Wang (2012)	2012	88	Taiwan	Eastern	HEL
10	Cheng (2012)	2012	483	Taiwan	Eastern	OL
11	Ramayah et al. (2012)	2012	194	Malaysia	Eastern	OL
12	Lin & Chen (2012).	2012	412	Taiwan	Eastern	HEL
13	Chen & Kao (2012)	2012	185	Taiwan	Eastern	OL
14	Eom, Ashill, Arbaugh, & Stapleton, (2012)	2012	674	USA	Western	HEL
15	Chen (2012)	2012	186	Taiwan	Eastern	OL
16	Estelami & Eom (2012)	2012	140	USA	Western	HEL
17	Chen, Mou Te Chang, Chen, Huang, & Chen (2012a)	2012	416	Taiwan	Eastern	HEL
18	Li, Duan, Fu, & Alford (2012)	2012	280	China	Eastern	HEL
19	Chen, Shih, & Yu (2012b)	2012	87	Taiwan	Eastern	HEL
20	Lwoga (2013)	2013	408	Africa	Eastern	HEL
21	Balaban et al. (2013)	2013	186	USA, Europe	Western	HEL
22	Cheng (2014)	2014	378	Taiwan	Eastern	OL
23	Samadi, Masrek, & Yatin (2014)	2014	425	Iran	Eastern	HEL
24	Wang et al. (2014)	2014	240	Taiwan	Eastern	HEL
25	Mohammadi (2015a)	2015	390	Iran	Eastern	HEL
26	Chuo et al. (2015)	2015	358	Taiwan	Eastern	OL
27	Huang, Pu, Chen, & Chiu (2015)	2015	206	Taiwan	Eastern	HEL
28	Shin & Kang (2015)	2015	1117	Korea	Eastern	HEL
29	Mohammadi (2015b)	2015	390	Iran	Eastern	HEL
30	Chen & Chengalur-Smith (2015)	2015	239	USA	Western	HEL
31	Marjanovic et al. (2016)	2016	279	Serbia	Western	OL
32	Alzu'Bi & Hassan (2016)	2016	431	Jordan	Eastern	HEL
33	Masrek & Gaskin (2016)	2016	346	Malaysia	Eastern	HEL
34	Dağhan & Akkoyunlu (2016)	2016	467	Turkey	Western	HEL
35	Chiu et al. (2016)	2016	123	Taiwan	Eastern	HEL
36	Yang, Shao, Liu, & Liu (2017)	2017	294	China	Eastern	HEL
37	Lin, Wang, Li, Shih, & Lin (2017)	2017	450	Taiwan	Eastern	HEL
38	Zheng & Liang (2017)	2017	572	China	Eastern	HEL
39	Mahmoodi et al. (2017)	2017	127	Iran	Eastern	HEL

Table B1. Information about Studies in the Meta-Analysis

40	Ahmed & Seliaman (2017)	2017	260	Saudi Arabia	Eastern	HEL
41	Ramírez-Correa, Rondan-Cataluña, Arenas-Gaitán, & Alfaro-Perez (2017)	2017	258	Chile	Eastern	HEL
42	Garcia & Silva (2017)	2017	108	Brazil	Eastern	HEL
43	Garcia & Silva (2017)	2017	108	Brazil	Eastern	HEL
44	Aldholay, Isaac, Abdullah, & Ramayah (2018a)	2018	448	Yemen	Eastern	HEL
45	Hammouri & Abu-Shanab (2018)	2018	386	Jordan	Eastern	HEL
46	Rana & Dwivedi (2018)	2018	138	UK	Western	HEL
47	Aldholay, Isaac, Abdullah, Abdulsalam, & Al-Shibami (2018b)	2018	448	Yemen	Eastern	HEL
48	Yakubu & Dasuki (2018)	2018	366	Nigeria	Eastern	HEL
49	Tsai, Chao, Lin, & Cheng (2018)	2018	557	Taiwan	Eastern	OL
50	Ghazal, Aldowah, Umar, & Bervell (2018)	2018	174	Malaysia	Eastern	HEL
51	Lashayo, Alkawaz & Johar (2018)	2018	142	Tanzania	Eastern	HEL
52	Gan & Balakrishnan (2018)	2018	328	Malaysia	Eastern	HEL
53	Lee, Lee, & Kim (2018)	2018	204	South Korea	Eastern	HEL
54	Alzahrani et al. (2019)	2019	978	Malaysia	Eastern	HEL
55	Thongsri, Shen, & Bao (2019)	2019	307	Thailand	Eastern	HEL
56	Isaac et al. (2019)	2019	448	Yemen	Eastern	HEL
57	Wang et al. (2019)	2019	160	Taiwan	Eastern	HEL and OL
58	Martins et al. (2019)	2019	403	Portugal	Western	HEL
59	Kurt (2019)	2019	144	Italy	Western	HEL
60	Aldholay et al. (2019)	2019	448	Yemen	Eastern	HEL
61	Doleck et al. (2019)	2019	169	Canada	Western	HEL

Note: HEL = higher education learners, OL = organizational learners.

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