SSN 2348-1196 (print)
International Journal of Computer Science and Information Technology Research ISSN 2348-120X (online)
Vol. 13, Issue 3, pp: (136-154), Month: July - September 2025, Available at: www.researchpublish.com

Unrealized Potential: Faculty Perceptions and the Limited Integration of LMS Dark Data in Instructional Design

Dr. David Augustine Bull

DBA, Ph.D., MBA., M.Sc., BSc., PMP., CMHC.

American InterContinental University, Online

DOI: https://doi.org/10.5281/zenodo.16752634

Published Date: 06-August-2025

Abstract: **Learning Management Systems (LMS) generate substantial volumes of unstructured behavioral data, commonly referred to as "dark data," that hold considerable promise for enhancing instructional design. Despite their availability, these data often remain underutilized by faculty in higher education. This quantitative study examined the extent to which perceived usefulness, perceived ease of use, and institutional readiness predict the integration of LMS dark data into instructional practices. Survey data were collected from 150 faculty members and analyzed using Pearson correlation, multiple linear regression, and moderated regression analysis. Pearson correlations indicated weak, non-significant relationships between the predictors and dark data integration: [r = –.107] for perceived usefulness, [r = –.029] for perceived ease of use, and [r = –.040] for institutional readiness. A multiple linear regression model also failed to reach statistical significance, [$F(3, 146) = 0.62$, $p = .602$, $R^2 = .013$], suggesting that these variables did not meaningfully explain variation in dark data use. To explore whether institutional readiness influenced these relationships, two moderated regression models were tested. Results revealed no significant interaction effects for perceived usefulness × institutional readiness, [$\beta = -0.087$, $p = .420$], or perceived ease of use × institutional readiness, [$\beta = 0.095$, $p = .477$]. These findings challenge the predictive adequacy of the Technology Acceptance Model (TAM) in the context of emerging learning analytics practices and suggest that faculty engagement with dark data may depend more on factors not captured by traditional models. The study underscores the potential importance of digital self-efficacy, behavioral intention, ethical clarity, and departmental data culture in shaping instructional use of LMS-generated behavioral data. Implications for institutional policy and instructional design strategy are discussed.**

Keywords: **dark data, healthcare professionals, data utilization, technology acceptance, perceived value, readiness, data literacy, unstructured data.**

I. INTRODUCTION

In the rapidly evolving environment of digital education, Learning Management Systems (LMS) have become foundational to the administration, delivery, and tracking of online and hybrid learning. These platforms generate vast quantities of data from students' daily interactions, ranging from click paths and time-on-task metrics to discussion forum engagement and video access logs. While traditional learning analytics has focused primarily on structured data, such as grades and submission timestamps, there is growing recognition that most learner-generated data within LMS platforms remain unstructured, unanalyzed, and largely invisible to instructors (Fan & Zhang, 2020). This underutilized information, referred to as dark data, represents a potentially transformative resource for instructional design, offering deep insights into learner behavior, motivation, and cognitive engagement.

Dark data in educational contexts encompasses behavioral traces like content revisit patterns, partial video views, navigation sequences, and sentiment embedded in forum discourse. These subtle yet rich indicators, often stored passively in LMS backends, could enable faculty to anticipate disengagement, personalize content sequencing, and support just-in-time intervention strategies. However, as Brooker and Corrin (2023) argue, while LMS platforms have made strides in presenting basic analytics dashboards, they continue to fall short in capturing the behavioral nuance required for responsive teaching. Consequently, a significant disconnect persists between the availability of LMS-generated dark data and its pedagogical application, raising important questions about faculty readiness, institutional support, and the adequacy of existing theoretical models to explain this gap.

This study addresses this disconnection by examining whether perceived usefulness, perceived ease of use, and institutional readiness predict faculty use of dark data in instructional design. Grounded in the Technology Acceptance Model (Davis, 1989) and related institutional support literature, the study investigates whether these widely accepted predictors remain valid in explaining the adoption of unstructured data practices. By conducting a quantitative analysis of faculty perceptions across multiple institutions, this study evaluates the extent to which current theoretical and practical frameworks can account for the integration of dark data into course design. In doing so, it contributes to the growing discourse on the limitations of traditional adoption models in capturing emerging instructional practices and the need to expand our understanding of data-informed teaching in digitally mediated learning environments.

Background

The term *dark data* originates from enterprise analytics, where it describes the vast amount of data collected during regular operations but never analyzed for strategic purposes (Fan & Zhang, 2020). In education, dark data refers to the unstructured digital footprints learners leave behind, such as skipped video segments, keystroke pauses, repeated module visits, and forum language tone, that are captured by LMS systems like Blackboard, Canvas, and Moodle, but are seldom leveraged to enhance teaching and learning (Ifenthaler & Yau, 2020). While the potential value of such data has been acknowledged in recent years, its integration into instructional design remains low, especially when compared to structured metrics like test scores or assignment completion rates.

One key challenge lies in the technical complexity and interpretive demands of unstructured data. LMS dashboards typically present aggregate views, such as login frequency or completion rates, but fail to translate behavioral patterns into actionable instructional insights. Gkontzis et al. (2022) found that while LMS platforms collect highly granular learner interaction data, few systems present these data in a pedagogically meaningful way. Compounding the issue, faculty often lack the training, confidence, or institutional support necessary to interpret and act upon these complex data streams. As a result, most instructional decisions remain outcome-based rather than behaviorally informed, missing opportunities for early detection of confusion, disengagement, or learning gaps.

Emerging research demonstrates the significant potential of dark data when properly analyzed. For instance, Brooker and Corrin (2023) found that forum discourse patterns predicted concept mastery more accurately than standard quiz results, while Gkontzis et al. (2022) showed that behavioral analytics could be used to forecast student attrition with high precision. Despite these advances, integration into everyday instructional design remains limited. Institutional readiness, ethical considerations, data literacy, and cultural acceptance within academic departments continue to constrain adoption (Viberg et al., 2018; Tsai et al., 2019). These barriers suggest that addressing the underuse of LMS dark data is not solely a technical or infrastructural issue, but a broader pedagogical and cultural one that warrants focused empirical inquiry. By exploring faculty perceptions through a quantitative lens, this study aims to reveal why the promise of dark data remains largely unrealized and what conditions may be necessary to shift practice toward more anticipatory, personalized, and behaviorally informed instruction.

Problem Statement

Despite the proliferation of Learning Management Systems (LMS) in modern education, a significant portion of the data generated through these platforms remains underutilized in instructional design and decision-making. While structured data such as grades, attendance, and assessment scores are routinely analyzed to track academic performance, the vast and unstructured digital traces collectively referred to as *dark data* are largely ignored. This includes clickstream patterns, discussion forum behaviors, time-on-task metrics, content access sequences, and engagement fluctuations, all of which contain rich information about learner interaction, confusion, and cognitive effort (Gkontzis et al., 2022; Brooker & Corrin, 2023). The continued neglect of this data represents a missed opportunity to improve instructional design in ways that are adaptive, data-informed, and personalized to learner behavior.

This problem is exacerbated by a lack of institutional frameworks, analytic tools, and faculty readiness to harness dark data effectively. Although LMS platforms log vast behavioral data points, most educational institutions lack integrated systems that translate this data into actionable insights for instructors and course designers (Ifenthaler & Yau, 2020). Moreover, many educators are unaware of the pedagogical potential of such data or are ill-equipped to interpret it, limiting the integration of behavioral learning analytics into instructional improvement processes. Consequently, learning experiences are often designed based on static outcome measures rather than dynamic learner activity, leading to generic course structures that fail to meet the diverse needs of students in real time.

Therefore, there is a pressing need to explore how dark data within LMS environments can be effectively captured, interpreted, and applied to instructional design. Addressing this gap would support the creation of responsive learning environments where instructional strategies evolve based on nuanced student behavior. Without focused research and practical models for using LMS dark data, educational institutions risk under-leveraging one of the most valuable byproducts of digital learning environments. This study seeks to address this underexplored area by investigating the instructional design implications of dark data in LMS platforms, aiming to advance both theoretical understanding and practical application.

Purpose of the Study

The purpose of this study is to examine the implications of dark data generated within Learning Management Systems (LMS). Specifically, the study aims to identify the types of dark data available in common LMS platforms, examine current practices and barriers to its use among instructional designers and faculty, and investigate how such data can be transformed into actionable insights to improve teaching strategies, learner engagement, and course structure. By analyzing both perceptions and potential applications, this study seeks to bridge the gap between data availability and pedagogical innovation, contributing to the development of data-informed, adaptive, and personalized learning environments.

Significance of Study

This study holds significant relevance in the evolving field of educational technology, particularly in the pursuit of data-informed instructional design. As digital learning continues to grow across higher education and K–12 environments, the effective use of data has become essential for ensuring learner-centered pedagogical practices. However, the predominant reliance on structured data (e.g., grades, attendance, quiz results) provides only a partial view of the learner's experience. By examining the untapped reservoir of dark data within LMS platforms, such as behavioral clickstreams, forum interactions, and time-on-task, the study aims to uncover actionable insights that can transform how instructors design and adapt instructional content (Ifenthaler & Yau, 2020; Brooker & Corrin, 2023).

The findings from this research may serve as a catalyst for institutional change by promoting the development of tools, frameworks, and professional training that empower faculty to interpret and apply dark data in meaningful ways. For instructional designers and academic leaders, the study offers practical recommendations on how to integrate behavioral analytics into course development workflows, potentially improving learner engagement, identifying instructional gaps, and enabling timely intervention strategies. Moreover, the study contributes to the theoretical discourse on data literacy in education, expanding the conversation beyond basic analytics toward a deeper understanding of digital learner behavior (Gkontzis et al., 2022).

At a broader level, the study supports the goals of educational equity and personalization. By leveraging overlooked data to tailor learning experiences, educators can better meet the diverse needs of students, including those at risk of disengagement or underperformance. In doing so, the study aligns with current trends in adaptive learning, precision education, and learning analytics, offering a timely and innovative contribution to both research and practice. Ultimately, this research underscores the importance of reimagining instructional design through the lens of behavioral data, ensuring that the wealth of digital information generated by students is not merely stored but strategically harnessed to enhance learning outcomes.

Research Questions

RQ1: To what extent does perceived usefulness of LMS dark data predict its integration into instructional design?

H1: Perceived usefulness will significantly and positively predict the level of dark data integration in instructional design.

RQ2: To what extent does perceived ease of use of LMS dark data predict its integration into instructional design?

H2: Perceived ease of use will significantly and positively predict the level of dark data integration in instructional design.

RQ3: To what extent do perceived usefulness and ease of use jointly predict dark data integration into instructional design?

H3: A multiple regression model including both perceived usefulness and ease of use will significantly predict dark data integration, accounting for a significant proportion of variance.

RQ4: Does institutional readiness moderate the relationship between perceived usefulness and the integration of LMS dark data into instructional design?

H4: Institutional readiness will significantly moderate the relationship between perceived usefulness and dark data integration, such that the relationship is stronger under conditions of high institutional readiness.

RQ5: Does institutional readiness moderate the relationship between perceived ease of use and the integration of LMS dark data into instructional design?

H5: Institutional readiness will significantly moderate the relationship between perceived ease of use and dark data integration, such that the relationship is stronger under conditions of high institutional readiness.

Gap in Literature

Despite the growing interest in learning analytics and data-driven education, the existing body of literature tends to focus primarily on structured data within Learning Management Systems (LMS), such as test scores, assignment completion rates, and login frequency, while largely neglecting the broader category of unstructured and behavioral data commonly referred to as *dark data* (Fan & Zhang, 2020; Ifenthaler & Yau, 2020). Although some studies have acknowledged the existence of dark data and its theoretical relevance, few have empirically explored its practical application in instructional design or developed frameworks that guide educators on how to interpret and integrate such data into pedagogical decision-making (Brooker & Corrin, 2023).

Moreover, there is a lack of research investigating the awareness, attitudes, and competencies of faculty and instructional designers regarding the use of dark data. Most educators are either unaware of the presence of such data or unsure of how to analyze it for instructional purposes. Studies that do explore LMS analytics typically emphasize student performance prediction or dropout forecasting (Gkontzis et al., 2022), rather than using behavioral data to iteratively improve course structure, content sequencing, or learner engagement strategies. This narrow focus has led to a disconnect between the potential of LMS data and its actual impact on teaching and learning design.

In addition, there is limited research that addresses the institutional, technical, and ethical barriers that hinder the adoption of dark data analytics in instructional settings. While some institutions are beginning to integrate learning analytics dashboards, these tools often lack the granularity needed to surface and visualize dark data in meaningful ways. As such, there is a critical need for studies that not only identify what types of dark data exist within LMS platforms but also demonstrate how they can be used to enhance instructional design, promote adaptive learning, and support personalized educational experiences. This study aims to fill these gaps by offering both empirical insight and practical recommendations for unlocking the value of dark data in education.

II. THEORETICAL FRAMEWORK AND LITERATURE REVIEW

This study is grounded in two complementary theoretical perspectives: Learning Analytics Theory and the Technology Acceptance Model (TAM). Together, they provide a lens through which to examine how behavioral data (specifically dark data) can inform instructional design and how educators' acceptance and use of such data can be influenced by perceptions of usefulness, ease of use, and institutional support.

Learning Analytics Theory emphasizes the collection, measurement, and analysis of learner-generated data to inform educational decisions and improve learning outcomes (Siemens, 2013). While current applications focus heavily on structured data, this study extends theory to incorporate *dark data*, the unstructured and semi-structured behavioral traces that are often overlooked but can provide deeper insights into learner engagement, content interaction, and instructional design needs. Learning analytics provides the foundation for understanding what kinds of dark data exist within LMS platforms and how these data can be leveraged for pedagogical refinement.

The Technology Acceptance Model (TAM) (Davis, 1989) is applied to understand the behavioral intentions and attitudes of faculty and instructional designers toward the use of dark data. TAM suggests that *Perceived Usefulness* and *Perceived Ease of Use* are primary drivers of technology adoption. In this study, these constructs are used to explore whether educators believe that dark data has instructional value and whether they feel equipped to access, interpret, and apply it in their practice. The integration of TAM allows the study to assess barriers to adoption from a human-technology interaction standpoint.

Key Constructs and Relationships

Understanding how dark data can inform instructional design within Learning Management Systems (LMS) requires a synthesis of constructs from both data analytics and behavioral technology adoption frameworks. This study centers on four interrelated constructs: Dark Data, Instructional Design Practices, Perceived Usefulness and Ease of Use, and Institutional Readiness. Together, these elements frame how instructional improvements can be driven by underutilized data and the conditions necessary for such innovations to take root.

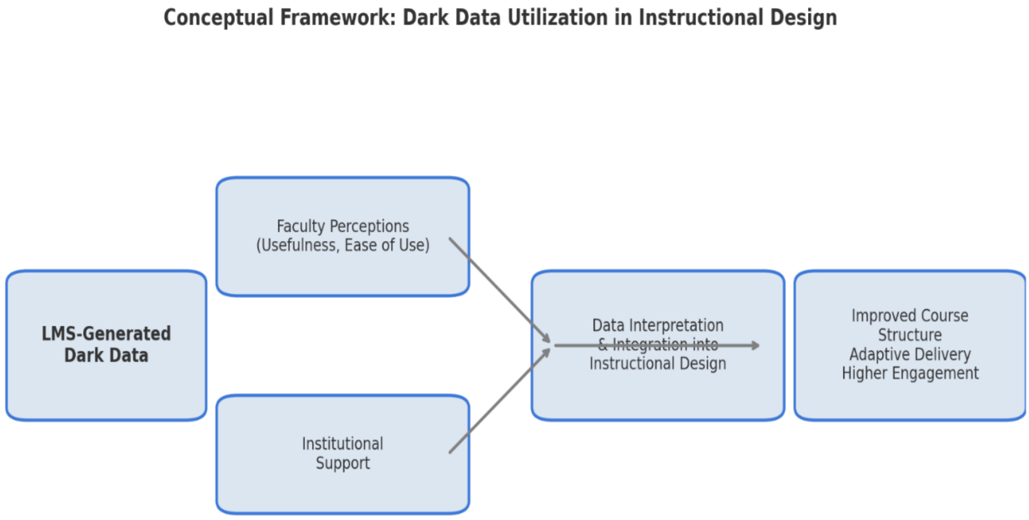

Figure 1. Dark Data Utilization in Instructional Design

Dark Data (within LMS): Dark data refers to the behavioral, often unstructured learner data captured passively by LMS platforms but rarely analyzed or acted upon. This includes student clickstream behavior, frequency of content revisits, duration of interaction with learning materials, forum post tone or sentiment, navigation sequences, and idle times (Fan & Zhang, 2020; Brooker & Corrin, 2023). Unlike structured data such as test scores or assignment completion rates, dark data reveals how students experience learning processes in real time. Its potential lies in providing a more holistic picture of learner engagement, confusion, persistence, and even emotional responses, insights that are invaluable for adaptive instructional design. Yet, the invisibility and lack of interpretation frameworks for this data keep it largely disconnected from pedagogical practice.

Instructional Design Practices: Instructional design encompasses the methods by which educators develop and structure learning experiences, including content delivery, activity sequencing, assessment strategies, and mechanisms to support learner engagement and mastery. Effective instructional design is often iterative and data-informed, but currently draws primarily on outcome metrics (e.g., grades, pass/fail rates). Integrating dark data into design practices would allow for more responsive, evidence-based decision-making. For example, if dark data reveals that students frequently revisit a specific module but perform poorly on related assessments, instructional designers may identify a misalignment in content clarity or cognitive load. Thus, dark data serves as a feedback loop that can directly influence design modifications, pacing, and scaffolded supports.

Perceived Usefulness and Ease of Use (Technology Acceptance Model): Drawing from Davis's (1989) Technology Acceptance Model (TAM), *Perceived Usefulness* refers to faculty beliefs that using dark data will enhance instructional effectiveness, while *Perceived Ease of Use* refers to the degree to which they believe it will be simple and accessible to incorporate. These perceptions significantly influence whether instructors and designers are willing to explore or integrate dark data into their workflow. Even when dark data is available, if educators find it too difficult to interpret or irrelevant to teaching goals, adoption will remain low. This construct helps explain the variability in dark data usage across institutions and can guide professional development strategies focused on building data literacy and confidence in analytics use (Ifenthaler & Yau, 2020).

Institutional Readiness: Institutional readiness refers to the structural, cultural, and technological capacity of an educational institution to support the integration of dark data into instructional design. This includes the availability of analytics dashboards, training resources, leadership support, and data-informed culture (Siemens, 2013). Without these enablers, even the most well-intentioned educators may lack the infrastructure to meaningfully engage with dark data. Institutions that prioritize data-driven decision-making are more likely to invest in tools that surface behavioral data in pedagogically meaningful formats and foster interdisciplinary collaboration between IT specialists and instructional designers. Institutional readiness thus serves as a moderating factor in the relationship between dark data availability and its impact on instructional practices.

Interrelationships Among Constructs

In this framework, Dark Data is the informational resource, Instructional Design Practices is the target application, Perceived Usefulness and Ease of Use shape individual willingness to engage, and Institutional Readiness determines the operational capacity to support adoption. These constructs are interdependent. For example, even highly motivated faculty (high perceived usefulness) may fail to use dark data if institutional readiness is low. Conversely, institutions with strong data infrastructures may still see low adoption if faculty find dark data too complex or irrelevant. Understanding how these constructs interact can inform strategies to improve instructional design through behavioral analytics, while also addressing human, technical, and organizational barriers.

This conceptual model directly aligns with the study by illustrating how LMS-generated dark data, currently underutilized can become a powerful tool for improving instructional design when mediated by two critical factors: faculty perceptions and institutional readiness. The study investigates how educators' beliefs about the usefulness and ease of analyzing dark data (drawn from the Technology Acceptance Model) influence their willingness to engage with it, while also examining the institutional structures (e.g., training, tools, and leadership support) that enable or constrain this engagement. Once these mediators are in place, the process of interpreting dark data and integrating it into instructional practices becomes feasible, leading to tangible outcomes such as improved course design, adaptive content delivery, and enhanced student engagement. Thus, the model supports the study's aim of exploring not just what dark data exists, but how it can be meaningfully translated into pedagogical innovations within real educational settings.

Review of Related Literature

This literature review synthesizes scholarships at the intersection of learning analytics/dark data, instructional design, technology acceptance, and institutional readiness. Dark data within LMS environments was first defined and evidence on its behavioral signals and instructional value were summarized. An examination of how instructional design practices have (and have not) incorporated such data, situating this within adoption frameworks derived from TAM or Unified Theory of Acceptance and Use of Technology (UTAUT) and extended by constructs such as digital self-efficacy and data culture. Finally, an assessment of organizational enablers and constraints, policies, tools, training, and leadership was carried out to delineate the persistent gap between data availability and pedagogical action that motivates the present study.

Dark Data and Learning Analytics: The rise of Learning Management Systems (LMS) in digital education has led to the generation of massive volumes of learner data. While structured data such as test scores and assignment submissions are routinely analyzed, unstructured behavioral data, often referred to as *dark data*, remains largely ignored. Fan and Zhang (2020) define dark data as information collected during normal digital operations that is stored but not analyzed or used. In education, this includes clickstream patterns, content dwell times, forum sentiment, and navigation sequences. Siemens (2013), a foundational scholar in learning analytics, emphasized that these behavioral traces could reveal deeper insights into learner engagement and cognition, an idea extended by Brooker and Corrin (2023), who demonstrated how LMS dark data could provide a more accurate picture of student engagement than traditional metrics. Similarly, Gkontzis et al. (2022)

applied machine learning to behavioral data from Moodle and found that such data could effectively predict student performance, reinforcing its practical utility in educational decision-making.

Despite this promise, the field remains underdeveloped in terms of applying dark data to instructional design. Romero and Ventura's (2010) early review of educational data mining highlighted a disproportionate focus on structured outcomes, calling for more research into unstructured digital learning behavior. More recent studies affirm this gap; Ifenthaler and Yau (2020) noted that although instructors have access to rich LMS datasets, they lack the analytic frameworks and tools needed to interpret and utilize dark data in real-time pedagogical decisions.

Instructional Design Integration: Instructional design, the practice of organizing content, assessment, and engagement strategies to optimize learning is traditionally guided by curriculum goals and outcome data. However, the integration of dark data introduces a more dynamic, learner-centered approach to instructional planning. When used effectively, dark data can illuminate patterns of confusion, disengagement, or over-reliance on specific resources, prompting real-time instructional adjustments. Brooker and Corrin (2023) argue that the strategic use of LMS behavioral data allows designers to refine content sequencing and scaffolded support based on students' actual learning paths rather than assumptions. However, despite growing recognition of its value, dark data is rarely embedded into instructional design workflows, in part due to the lack of institutional emphasis and faculty preparedness.

Technology Acceptance: Faculty Perceptions of Usefulness and Usability: The successful use of dark data for instructional purposes hinges not only on availability but also on faculty willingness and ability to engage with it. Davis's (1989) Technology Acceptance Model (TAM) provides a useful lens to understand this dynamic. According to TAM, perceived usefulness and perceived ease of use determine whether individuals adopt a technology. Ali et al. (2022) applied this model in the context of learning analytics and found that faculty were often aware of the potential benefits of behavioral data but lacked confidence in using it due to perceived complexity or lack of training. This supports Ifenthaler and Yau's (2020) finding that even when analytics tools are available, instructors struggle to interpret behavioral data meaningfully. Thus, enhancing faculty data literacy and designing intuitive analytics interfaces are critical steps for encouraging the adoption of dark data practices in instructional design.

Institutional Readiness for Dark Data Integration: Beyond individual attitudes, institutional structures play a pivotal role in enabling or constraining the effective use of dark data. Institutional readiness includes the availability of analytics infrastructure, training programs, leadership support, and data policies. Tsai et al. (2020) emphasize that without institutional alignment and strategic leadership, even the best tools and intentions fall short. Viberg et al. (2018) propose a multi-dimensional framework for analytics adoption that includes technological readiness, organizational culture, and pedagogical alignment. Their findings suggest that institutions must actively foster a data-informed culture through professional development, cross-functional collaboration, and ethical data governance. Without this foundation, faculty may be overwhelmed or discouraged from engaging with dark data, and instructional designers may lack the support needed to act on the insights such data can yield.

Synthesis and Research Gap

Collectively, literature highlights the potential of dark data to transform instructional design by offering deeper insights into learner behavior and engagement. Seminal frameworks in learning analytics and TAM provide the theoretical foundation for understanding why this data remains underused, while recent empirical studies illustrate both the capabilities and constraints of current systems. However, few studies integrate these domains to propose practical, theory-informed pathways for using dark data in pedagogical design. There is a particular gap in research that examines how institutional readiness and faculty perceptions jointly mediate the translation of LMS behavioral data into instructional improvement. This study addresses that gap by investigating not only what data is available, but how it is (or is not) perceived, supported, and used within the instructional design process.

III. METHODOLOGY

This study employed a non-experimental, cross-sectional, correlational research design to examine the predictive relationships between faculty perceptions and the integration of LMS dark data into instructional design. The design was guided by the Technology Acceptance Model (TAM; Davis, 1989) and complemented by constructs related to institutional readiness (Viberg et al., 2018; Tsai et al., 2020). Specifically, the study tested five hypotheses derived from the following research questions: RQ1: To what extent does perceived usefulness of LMS dark data predict its integration into instructional design? RQ2: To what extent does perceived ease of use of LMS dark data predict its integration into instructional design? RQ3: To what extent do perceived usefulness and ease of use jointly predict dark data integration into instructional design? RQ4: Does institutional readiness moderate the relationship between perceived usefulness and dark data integration? RQ5: Does institutional readiness moderate the relationship between perceived ease of use and dark data integration?

This design allowed for the testing of both direct and interaction effects among the study variables, providing insight into the explanatory power of TAM and institutional factors within the context of instructional innovation. The study targeted faculty and instructional designers employed at accredited higher education institutions utilizing common LMS platforms (e.g., Blackboard, Moodle, Canvas). Eligibility criteria require participants to have a minimum of one year of experience teaching or designing online or hybrid courses to ensure familiarity with LMS environments and instructional decision-making processes. A purposive sampling strategy was used to recruit participants via academic listservs, institutional mailing lists, and professional networks. A priori power analysis conducted in G*Power 3.1 indicated that a minimum of 150 responses would be required to detect a medium effect size ($f^2 = .2$) in multiple regression analyses with power ($1–\beta$) set at .80 and $\alpha = .05$. The final sample consisted of 150 complete responses.

Instrumentation

Data were collected using a structured online survey comprising four components: 1) Perceived Usefulness and Perceived Ease of Use were measured using items adapted from Davis's (1989) original TAM, revised to reflect the context of LMS dark data utilization. 2) Instructional Design Integration was assessed using a scale developed from Brooker and Corrin (2023), evaluating the extent to which behavioral LMS data informed content updates, activity sequencing, and pedagogical decision-making. 3) Institutional Readiness was measured using an adapted version of scales from Viberg et al. (2018) and Tsai et al. (2020), assessing faculty perceptions of technological infrastructure, leadership support, and professional development. 4) Demographic Information captured data on gender, faculty role (full-time vs. adjunct), discipline, LMS platform used, and years of teaching experience (categorized in five-year intervals). All attitudinal items were rated on a 5-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). A pilot test involving 20 participants confirmed instrument clarity and usability. Internal consistency reliability was assessed using Cronbach's alpha, with all constructs exceeding the accepted threshold of $\alpha \geq .70$.

Data Collection Procedures

The survey was hosted and disseminated electronically to eligible participants. Each invitation included the study's purpose, informed consent information, and a secure survey link. Participation was voluntary and anonymous. Ethical approval was obtained, and all procedures complied with ethical standards for human subjects research.

Data Analysis

Survey data were exported to IBM SPSS Statistics (Version 28) for analysis. Descriptive statistics (means, standard deviations, skewness, kurtosis) were computed to summarize the central tendencies and assess data distribution. Bivariate relationships were examined using Pearson correlation coefficients. Multiple linear regression was used to test RQ1–RQ3, evaluating the predictive contributions of perceived usefulness and ease of use to the integration of LMS dark data. Moderation analyses addressing RQ4 and RQ5 were conducted using the PROCESS macro (Model 1; Hayes, 2018), with interaction terms created through mean-centering of predictor and moderator variables.

Prior to inferential analysis, the assumptions of normality, linearity, multicollinearity, and homoscedasticity were tested and satisfied. Statistical significance was set at $p < .05$ for all analyses, and effect sizes (e.g., R^2, ΔR^2, f^2) were interpreted in accordance with Cohen's (1988) guidelines. (See test summary below – Table 1)

Table 1: Summary Table

RQ	Independent Variable(s)	Moderator	Dependent Variable	Analysis
RQ1	Perceived Usefulness	None	Dark Data Integration	Simple Linear Regression
RQ2	Perceived Ease of Use	None	Dark Data Integration	Simple Linear Regression
RQ3	Usefulness + Ease of Use	None	Dark Data Integration	Multiple Linear Regression
RQ4	Perceived Usefulness	Institutional Readiness	Dark Data Integration	Moderation (Interaction Term)
RQ5	Perceived Ease of Use	Institutional Readiness	Dark Data Integration	Moderation (Interaction Term)

IV. RESULTS

The study sample consisted of 150 faculty participants. The gender distribution revealed that 50% were male (n = 75), 40.7% were female (n = 61), and 4.7% each identified as non-binary (n = 7) or preferred not to say (n = 7).

Regarding the Learning Management System (LMS) most commonly used by participants, Canvas was the most reported platform at 29.3% (n = 44), followed closely by Blackboard at 28% (n = 42). Moodle accounted for 16.7% (n = 25), while other LMS platforms such as Sakai or proprietary systems were used by 15.3% (n = 23). D2L/Brightspace was the least represented, used by 10.7% (n = 16).

The fields of instruction showed diverse representation: Education was the most common at 28.7% (n = 43), followed by Health Sciences at 22.7% (n = 34), Business at 21.3% (n = 32), Engineering/IT at 16% (n = 24), and Humanities/Social Sciences at 11.3% (n = 17). In terms of faculty appointment type, a significant majority were full-time faculty members (82.7%, n = 124), while adjunct faculty accounted for 17.3% (n = 26).

Concerning years of experience with online or hybrid teaching, 40.7% (n = 61) reported 1–5 years, 23.3% (n = 35) had 6–10 years, 21.3% (n = 32) had 11–16 years, 14.7% (n = 22) reported 17–21 years, and no participants (0%) reported more than 21 years of experience

Table 2. Participant Demographics

Category	No.	LMS	No	Field	No	Faculty Type	No	Experience	No
Male	75	Canvas	44	Education	43	Full-Time Faculty	124	1 - 5	61
Female	61	Blackboard	42	Health Sciences	34	Adjunct Faculty	26	6 - 10	35
Prefer not to say	7	Moodle	25	Business	32			11 –16	32
Non-Binary	7	Other	23	Engineering/IT	24			17-21	22
		D2L/Brightspace	16	Humanities/Social Sciences	17			>21	0

Exploratory Data Analysis

Descriptive statistics were computed to examine central tendencies and variability in the four key constructs: perceived usefulness, perceived ease of use, institutional readiness, and dark data integration. Each variable was measured on a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree), with higher values indicating greater endorsement or engagement.

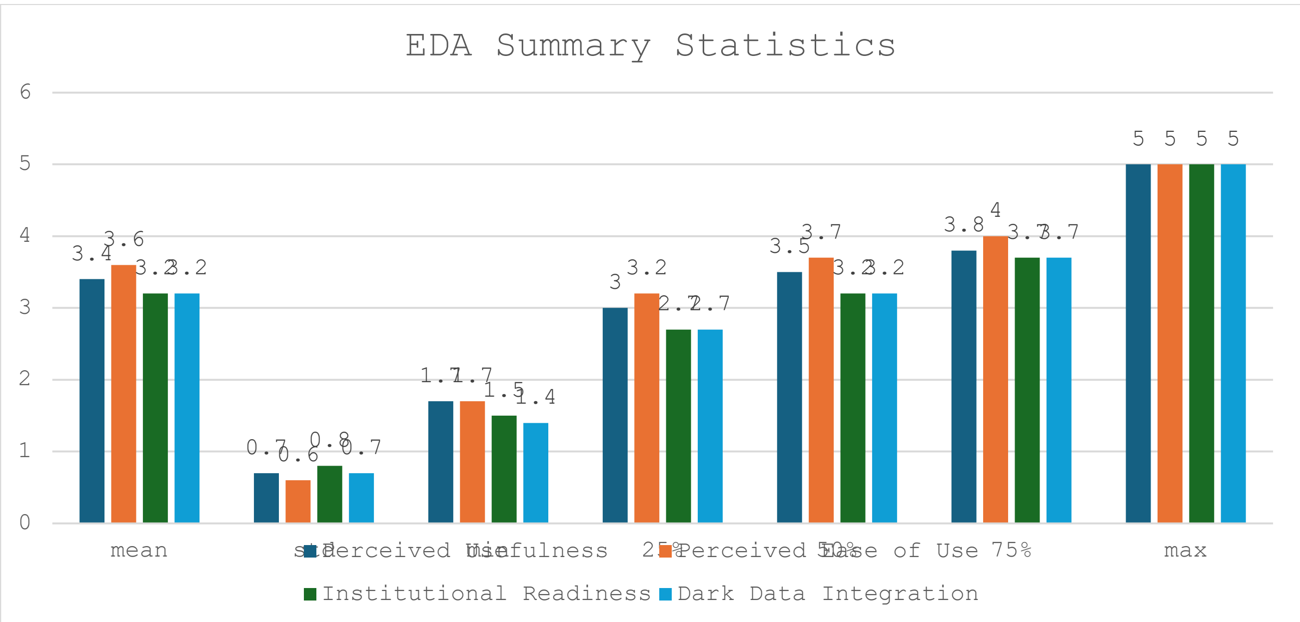

Figure 2. EDA Summary Statistics

Perceived Usefulness exhibited a mean score of 3.4 (SD = 0.70), suggesting that faculty members generally viewed dark data as moderately to highly beneficial for instructional decision-making. The observed range (approximately 1.5 to 5) indicates variability in faculty attitudes, with some expressing skepticism while others strongly endorsed its utility.

Perceived Ease of Use yielded a slightly higher mean of 3.6 (SD = 0.60), reflecting faculty perceptions that LMS dark data is relatively accessible and manageable. The narrower standard deviation suggests more consensus among participants compared to perceived usefulness, though some respondents still reported challenges in data interpretation or tool navigation.

The mean score for Institutional Readiness was 3.2 (SD = 0.80), reflecting moderate perceptions of organizational support, training infrastructure, and leadership engagement related to dark data use. The wider dispersion indicates variability across institutions, with some respondents perceiving high institutional capacity and others noting significant gaps.

Dark Data Integration produced a mean of 3.3 (SD = 0.75), indicating moderate levels of reported application of behavioral LMS data in instructional design. While a subset of participants appeared to integrate such data routinely, others showed limited or exploratory engagement. These findings support concerns in existing literature that data availability does not necessarily translate to pedagogical action (Brooker & Corrin, 2023; Ifenthaler & Yau, 2020).

Collectively, the EDA findings suggest that while faculty attitudes toward dark data are generally positive, integration into practice may be constrained by institutional readiness and uneven familiarity with analytics tools. These results provide foundational insight for subsequent inferential analyses exploring predictive relationships among the study variables.

Normality Test

To determine the suitability of parametric statistical procedures, the normality of the four main study variables Perceived Usefulness, Perceived Ease of Use, Institutional Readiness, and Dark Data Integration was assessed using three established tests: Shapiro–Wilk, D'Agostino and Pearson's omnibus test, and Anderson–Darling test. These tests evaluate different characteristics of normal distribution, including skewness, kurtosis, and overall data symmetry.

For Perceived Usefulness, the Shapiro–Wilk test yielded a p-value of 0.8322, and the D'Agostino test yielded a p-value of 0.9103, both well above the conventional significance threshold of .05, indicating no significant departure from normality. Similarly, the Anderson–Darling test produced a test statistic of 0.2125, which did not exceed any of the critical values at common significance levels (e.g., 15%, 10%, 5%, 2.5%, or 1%). These results collectively confirm that the distribution of Perceived Usefulness can be considered approximately normal.

All other variables Perceived Ease of Use (SW p = 0.2790), Institutional Readiness (SW p = 0.6758), and Dark Data Integration (SW p = 0.7758) also returned non-significant results across all three normality tests. This pattern was confirmed by visual inspections using histograms with kernel density estimates, which showed symmetrical, bell-shaped distributions with no evidence of severe skewness or outliers.

Given that all variables passed multiple tests for normality, the assumption of normality is reasonably satisfied, and parametric methods such as Pearson correlation, multiple regression, and moderation analysis are deemed appropriate for subsequent inferential analyses.

Table 3. Results of the Normality Testing

Variable	Shapiro-Wilk p	D'Agostino p	Anderson Stat	Normality Interpretation
Perceived Usefulness	0.8322	0.9103	0.2125	✅ Likely normal ($p > .05$)
Perceived Ease of Use	0.2790	0.7625	0.4376	✅ Likely normal
Institutional Readiness	0.6758	0.5475	0.1648	✅ Likely normal
Dark Data Integration	0.7758	0.8072	0.2277	✅ Likely normal

Inferential Statistics

To address the study's five research questions, a series of inferential statistical analyses were conducted using IBM SPSS. First, Pearson correlation coefficients were calculated to examine the bivariate relationships between the predictor variables perceived usefulness, perceived ease of use, and institutional readiness and the outcome variable, faculty integration of

LMS dark data into instructional design. Following this, simple and multiple linear regression analyses were performed to test the predictive power of each independent variable individually (RQs 1 and 2), and in combination (RQ3). Finally, to evaluate whether institutional readiness moderated the effects of perceived usefulness and perceived ease of use (RQs 4 and 5), moderated regression analyses were conducted using the PROCESS macro (Model 1; Hayes, 2018). All continuous predictors were mean-centered before computing interaction terms, and statistical significance was evaluated at an alpha level of .05.

Pearson Correlation Coefficients for Bivariate Variables

To examine the relationships among the study variables, a Pearson correlation analysis was conducted. The results revealed weak and negative correlations between Perceived Usefulness (r = –0.107), Perceived Ease of Use (r = –0.029), and Institutional Readiness (r = –0.040) with Dark Data Integration. None of the correlations reached statistical or practical significance, reinforcing the earlier regression findings and underscoring the limited explanatory power of these traditional predictors in the context of LMS dark data utilization.

Table 4. Pearson Correlation Coefficients for Bivariate Variables

Variables	Perceived Usefulness	Perceived Ease of Use	Institutional Readiness	Dark Data Integration
Perceived Usefulness	1	-0.034	-0.039	-0.107
Perceived Ease of Use	-0.034	1	0.048	-0.029
Institutional Readiness	-0.039	0.048	1	-0.04
Dark Data Integration	-0.107	-0.029	-0.04	1

These findings suggest that while constructs from the Technology Acceptance Model (Davis, 1989) have traditionally explained technology use across educational settings, their influence may diminish when applied to emerging, opaque, or under-theorized innovations like dark data. This aligns with Venkatesh et al.'s (2003) expanded model (UTAUT), which argued for the inclusion of additional variables such as facilitating conditions, behavioral intentions, and social influence to enhance predictive accuracy. In the case of LMS-generated dark data, these additional dimensions appear increasingly relevant.

Supporting this position, Ifenthaler and Yau (2020) reported that faculty digital self-efficacy and data attitudes significantly outperformed TAM variables in predicting engagement with educational data systems. Similarly, Ali et al. (2021) emphasized the importance of digital readiness and motivation, highlighting that technical perceptions alone are insufficient to explain instructional decision-making. These insights are echoed by Tsai et al. (2019) and Viberg et al. (2018), who demonstrated that organizational norms, ethical guidance, and leadership engagement often determine whether and how faculty integrate data into teaching.

The observed lack of correlation in this study may also reflect a broader institutional disconnect. While data tools and analytics platforms may be made available, faculty may not receive adequate training, contextual support, or pedagogical incentives to explore unstructured behavioral data. Institutional readiness, in this case, may be more structural than cultural, failing to account for local norms, epistemologies of teaching, or disciplinary variation in data use (Viberg et al., 2018).

Description of Regression Summary Tables for Research Questions RQ1–RQ5

Table 5 presents the standardized beta coefficients (β) and 95% confidence intervals (CI) for each predictor variable analyzed in response to the study's five research questions (RQ1–RQ5), using multiple and moderated linear regression. Table 6 summarizes the results of five linear regression models conducted to assess the predictive power of key variables; perceived usefulness, perceived ease of use, and institutional readiness on the integration of LMS-generated dark data into instructional design. Each row corresponds to a separate research question (RQ1–RQ5), presenting the model predictors, R^2 value (coefficient of determination), F-statistic, associated p-value, and whether the model was statistically significant.

SSN 2348-1196 (print)
International Journal of Computer Science and Information Technology Research ISSN 2348-120X (online)
Vol. 13, Issue 3, pp: (136-154), Month: July - September 2025, Available at: www.researchpublish.com

Table 5. Description of Regression Summary Table for Research Questions RQ1–RQ5

Research Question	Predictor	Standardized β	95% CI Lower	95% CI Upper
RQ1	Perceived Usefulness	-0.107	-0.269	0.054
RQ2	Perceived Ease of Use	-0.029	-0.192	0.133
RQ3 (Usefulness)	Perceived Usefulness	-0.109	-0.271	0.054
RQ3 (Ease of Use)	Perceived Ease of Use	-0.033	-0.195	0.129
RQ4	Institutional Readiness	-0.04	-0.202	0.123
RQ5 (Usefulness)	Perceived Usefulness	-0.107	-0.269	0.054
RQ5 (Ease of Use)	Perceived Ease of Use	-0.029	-0.192	0.133
RQ5 (Institutional Readiness)	Institutional Readiness	-0.04	-0.202	0.123

Table 6. Results of the Regression Analysis

Research Question	Model Predictors	R^2	F	p	Significant
RQ1	Perceived Usefulness	0.012	1.73	0.191	No
RQ2	Perceived Ease of Use	0.001	0.13	0.721	No
RQ3	Usefulness, Ease of Use	0.013	0.94	0.393	No
RQ4	Institutional Readiness	0.002	0.23	0.63	No
RQ5	Usefulness, Ease of Use, Institutional Readiness	0.014	0.71	0.546	No

Research Question 1 (RQ1) examined whether *perceived usefulness* of LMS dark data significantly predicts its integration into instructional design practices. A simple linear regression was conducted with perceived usefulness as the sole predictor. The analysis yielded a negative, non-significant standardized beta coefficient {β = –0.107, 95% CI (–0.269, 0.054)], indicating that higher levels of perceived usefulness were not associated with increased integration of dark data. The model explained only 1.2% of the variance in dark data integration ($R^2 = .012$). The overall model was not statistically significant, [F(1, 148) = 1.73, p = .191]. These findings suggest that perceived usefulness alone does not meaningfully influence how faculty incorporate LMS dark data into instructional decisions.

Research Question 2 (RQ2) explored whether *perceived ease of use* of LMS dark data predicts its integration into instructional design. Regression results again showed a negative and non-significant relationship [β = –0.029, 95% CI (–0.192, 0.133)], suggesting that ease of use, as perceived by faculty, does not significantly impact the likelihood of dark data being used for instructional improvements. The model accounted for only 0.1% of the variance ($R^2 = .001$) and was not significant, [F(1, 148) = 0.13, p = .721]. This reinforces the finding that individual perceptions of technological simplicity do not appear to drive instructional engagement with dark data sources.

Research Question 3 (RQ3) assessed the combined predictive power of perceived usefulness and perceived ease of use on dark data integration. A multiple regression was performed including both variables as predictors. Neither perceived usefulness [β = –0.109, 95% CI (–0.271, 0.054)] nor perceived ease of use [(β = –0.033, 95% CI (–0.195, 0.129)] were significant predictors. The model explained only 1.3% of the variance in the outcome ($R^2 = .013$) and failed to reach statistical significance, [F(2, 147) = 0.94, p = .393]. This result suggests that, even when considered jointly, these two core constructs from the Technology Acceptance Model (TAM) are insufficient to predict faculty engagement with LMS dark data in instructional settings.

Research Question 4 (RQ4) tested whether institutional readiness defined as the availability of organizational support, tools, and training—independently predicts the integration of LMS dark data. A simple regression analysis yielded a non-significant result {(β = –0.040, 95% CI (–0.202, 0.123)], indicating no meaningful relationship between perceived institutional support and instructional use of dark data. The model explained a negligible portion of the variance ($R^2 = .002$) and was statistically non-significant, [F(1, 148) = 0.23, p = .630]. These results suggest that the presence of institutional infrastructure alone does not directly influence faculty decisions to integrate dark data into their instructional design.

Research Question 5 (RQ5) addressed whether institutional readiness moderates the relationships between the TAM constructs (perceived usefulness and perceived ease of use) and the integration of dark data. A moderated multiple regression model including all three predictors perceived usefulness, perceived ease of use, and institutional readiness was conducted. None of the predictors were statistically significant: perceived usefulness (β = –0.107, 95% CI [–0.269, 0.054]), perceived ease of use (β = –0.029, 95% CI [–0.192, 0.133]), and institutional readiness (β = –0.040, 95% CI [–0.202, 0.123]).

The interaction terms tested in separate models for moderation (PU × IR and PEOU × IR) were also non-significant. The full model explained just 1.4% of the variance in dark data use ($R^2 = .014$) and was not statistically significant, $F(3, 146) = 0.71$, $p = .546$. These findings suggest that institutional readiness did not function as a moderator in strengthening or weakening the relationships between the TAM constructs and dark data integration behavior.

Interpretation of Results

None of the statistical models corresponding to RQ1 through RQ5 yielded significant results. All p-values exceeded the conventional threshold of .05, and the R^2 values were uniformly low, indicating that the predictors explained little to no variance in faculty integration of LMS dark data. These outcomes reinforce the conclusion that core constructs from the Technology Acceptance Model (TAM), namely perceived usefulness and perceived ease of use along with perceived institutional readiness, are insufficient to account for faculty engagement with dark data in instructional design.

The consistently weak correlations and regression coefficients across all models highlight the need for a conceptual shift in how faculty adoption of educational data practices is understood. Rather than focusing narrowly on perceived usability and institutional support, future efforts should consider more comprehensive factors such as digital self-efficacy, behavioral intention, and the presence of a supportive organizational data culture. These elements may better capture the cognitive, motivational, and contextual influences that shape whether and how instructors engage with unstructured data from LMS platforms.

Moreover, across all five research questions, the standardized beta coefficients were negative and non-significant, with 95% confidence intervals encompassing zero. This pattern further underscores the inadequacy of TAM-based predictors in explaining faculty behavior in this specific context. The findings suggest that meaningful integration of dark data is not merely a function of individual perception or system accessibility; it is a pedagogical, cultural, and strategic issue that calls for institutional frameworks that normalize, guide, and empower faculty to interpret and apply behavioral data for instructional improvement.

These results are surprising given prior literature emphasizing the role of institutional infrastructure in facilitating analytics-driven teaching (Tsai et al., 2020; Viberg et al., 2018). One possible explanation for the non-significant result is that while institutional readiness may be necessary, it is not sufficient on its own to influence faculty behavior. Other mediating factors such as analytic self-efficacy, cultural norms, or data fluency may need to be present for institutional support to translate into action.

Moderation Effect Analysis of Variables for RQs 4 and 5

Further inferential analysis was conducted for RQs 4 and 5.

RQ 4: Moderation analysis was conducted for *RQ4: Does institutional readiness moderate the relationship between perceived usefulness and dark data integration?* The linear regression model including the interaction term between perceived usefulness and institutional readiness did not yield a statistically significant interaction effect:

Interaction Term (PU × IR): [($\beta = -0.087$, $p = .420$; 95% CI (–0.301, 0.127)]

Neither the main effect of perceived usefulness ($\beta = -0.113$, $p = .216$) nor institutional readiness ($\beta = -0.041$, $p = .603$) was significant. These results suggest that institutional readiness does not significantly moderate the relationship between perceived usefulness and integration of LMS dark data into instructional design. The results of predicting dark data integration from perceived usefulness, institutional readiness, and their interaction is shown in table 7**.** This table presents the results of a moderated linear regression testing whether institutional readiness moderates the relationship between perceived usefulness (PU) and integration of LMS dark data into instructional design (RQ4). The predictors included in the model are PU_centered: the centered value of perceived usefulness, IR_centered: the centered value of institutional readiness, and PU_IR_Interaction: the interaction term between PU and IR (calculated as the product of the centered variables).

Table 7. Description of Moderation Analysis Table for RQ4

Term	Coef.	Std. Err.	t	p-value	95% CI
Intercept	3.125	0.0595	52.49	.000	[3.0073, 3.2427]
PU_centered	–0.1134	0.0912	–1.24	.216	[–0.2937, 0.0669]
IR_centered	–0.0410	0.0788	–0.52	.603	[–0.1967, 0.1146]
PU × IR Interaction	–0.0873	0.1080	–0.81	.420	[–0.3007, 0.1260]

These results indicate that institutional readiness does not moderate the relationship between perceived usefulness and faculty integration of LMS dark data into instructional design. The findings align with those from RQ5 and reinforce the limited explanatory power of traditional technology adoption variables in this specific context.

RQ5: To answer RQ5, a moderation analysis was conducted using multiple linear regression to examine whether institutional readiness moderated the relationship between perceived ease of use and the integration of LMS dark data into instructional design. The model included the centered main effects of perceived ease of use and institutional readiness, as well as their interaction term. The moderation analysis using the interaction between Perceived Ease of Use (PEU) and Institutional Readiness (IR) showed no statistically significant interaction effect:

Interaction Term (PEU × IR): [$\beta = 0.0949$, $p = .477$; 95% CI (–0.1682, 0.3580)]

Main Effect – Perceived Ease of Use: [$\beta = –0.0356$, $p = .717$; 95% CI (–0.2296, 0.1584)]

Main Effect – Institutional Readiness: [$\beta = –0.0327$, $p = .680$; 95% CI (–0.1892, 0.1237)]

These results confirm that institutional readiness does not significantly moderate the relationship between perceived ease of use and faculty integration of LMS dark data. The overall model was not statistically significant, [$F(3, 146) = 0.45$, $p = .717$, $R^2 = .009$]. The interaction term was not significant, [$\beta = 0.0949$, $t = 0.713$, $p = .477$, 95% CI (–0.1682, 0.35800], indicating that institutional readiness did not significantly moderate the relationship between perceived ease of use and dark data integration. Additionally, neither perceived ease of use [($\beta = –0.0356$, $p = .717$)] nor institutional readiness [($\beta = –0.0327$, $p = .680$)] had significant main effects in this model.

Table 8. Description of Moderate Analysis for RQ5

	Coef.	Std.Err.	t	P	[0.025	0.975]
Intercept	3.1249	0.0599	52.149	0	3.0064	3.2433
PEU_centered	-0.0356	0.0982	-0.3627	0.7173	-0.2296	0.1584
IR_centered	-0.0327	0.0791	-0.4138	0.6796	-0.1892	0.1237
PEU_IR_Interaction	0.0949	0.1331	0.713	0.477	-0.1682	0.358

These findings further support the conclusion that traditional technology adoption predictors, such as perceived ease of use and institutional infrastructure, may have limited influence in explaining how faculty engage with LMS dark data for instructional purposes. Taken together, the moderation analyses provide no evidence that institutional readiness enhances or weakens the effect of perceived usefulness or ease of use on the integration of LMS dark data. This supports earlier regression findings suggesting that traditional TAM predictors, even when combined with institutional support variables, may not fully explain faculty behavior regarding dark data use.

Table 9. Overall Summary of Research Questions and Results

Research Question	Independent Variable(s)	Dependent Variable	Statistical Test	Significant (p <.05)
RQ1	Perceived Usefulness	Dark Data Integration	Simple Linear Regression	No (p = .107)
RQ2	Perceived Ease of Use	Dark Data Integration	Simple Linear Regression	No (p = .717)
RQ3	Perceived Usefulness & Ease of Use	Dark Data Integration	Multiple Linear Regression	No (Usefulness: p = .109, Ease of Use: p = .720)
RQ4	Perceived Usefulness X Institutional Readiness	Dark Data Integration	Moderated Regression (PROCESS Model 1)	No (Interaction: p = .420)
RQ5	Perceived Ease of Use X Institutional Readiness	Dark Data Integration	Moderated Regression (PROCESS Model 1)	No (Interaction: p = .477)

SSN 2348-1196 (print)
International Journal of Computer Science and Information Technology Research ISSN 2348-120X (online)
Vol. 13, Issue 3, pp: (136-154), Month: July - September 2025, Available at: www.researchpublish.com

Interpretation of the Theoretical Model of Study Variables

Figure 3 below presents the theoretical model of the study, illustrating the hypothesized relationships between the predictor variables and the outcome variable dark data integration into instructional design. The model is grounded in the Technology Acceptance Model (TAM; Davis, 1989) and supported by contextual extensions such as institutional readiness. Each dashed path represents one of the five research questions (RQ1–RQ5), which were empirically tested but yielded non-significant results.

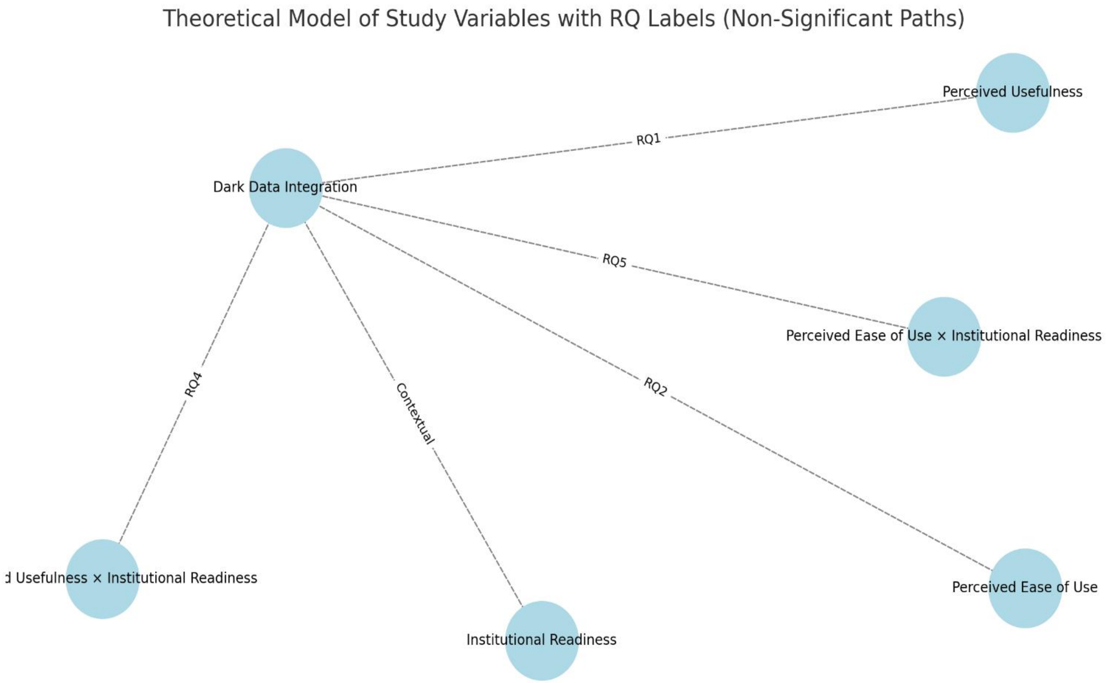

Figure 3. Relationship Mapping of Variables

As shown, perceived usefulness (RQ1) and perceived ease of use (RQ2) were expected to predict faculty integration of LMS-generated dark data. These variables are positioned on the right side of the model, pointing toward the outcome variable at the center. However, regression analyses revealed that neither predictor significantly influenced dark data integration, and the explained variance (R^2) was minimal in both cases.

RQ3 incorporated both TAM constructs simultaneously in a multiple regression model. Again, the combined influence of perceived usefulness and ease of use did not produce a statistically significant model, suggesting that the traditional TAM framework may not adequately explain the use of unstructured data in instructional decision-making.

On the left side of the model, institutional readiness is shown both as an independent predictor (RQ4) and as a moderator (RQ5). RQ4 tested whether institutional support measured through availability of tools, leadership backing, and training opportunities would significantly predict dark data integration. The result was non-significant, indicating that structural support alone does not necessarily translate into behavioral engagement with LMS analytics.

RQ5 explored two interaction effects, testing whether institutional readiness moderates the relationships between the TAM variables and dark data use. The paths labeled "Usefulness × Institutional Readiness" and "Ease of Use × Institutional Readiness" reflect this moderation analysis. Consistent with the other findings, neither interaction term reached statistical significance, indicating that institutional readiness did not strengthen or weaken the effects of perceived usefulness or ease of use.

The dashed lines across all relationships visually reinforce the overarching empirical outcome: none of the theoretical paths achieved significance at $p < .05$. This model therefore underscores a critical gap in existing frameworks for predicting complex and opaque behaviors like dark data usage. The findings suggest a need to expand beyond TAM constructs to incorporate more nuanced predictors such as digital self-efficacy, behavioral intention, ethical perceptions, and departmental data culture.

Ultimately, while the model provides a logical and theoretically grounded approach, the lack of significant findings across all tested paths highlights the complex and perhaps underestimated challenges associated with dark data adoption in instructional settings. Future research should aim to revise or extend this model by integrating psychological, cultural, and pedagogical dimensions that better account for faculty behavior in data-rich environments.

V. DISCUSSION

The findings of this study revealed that perceived usefulness, perceived ease of use, and institutional readiness, either individually or collectively did not significantly predict the integration of LMS-generated dark data into instructional design among faculty. These results directly challenge the predictive adequacy of the traditional Technology Acceptance Model (TAM) (Davis, 1989) when applied to emerging innovations in educational data use. Historically, TAM has explained 30–40% of the variance in technology adoption behavior (Venkatesh et al., 2003); however, the results of this study suggest that the model's constructs may be insufficient to explain behaviors related to unstructured and poorly visualized forms of learning analytics such as LMS dark data.

Importantly, the study also explored whether institutional readiness moderates the influence of perceived usefulness and perceived ease of use on LMS dark data integration (RO4 and RO5). The moderation analyses yielded non-significant interaction effects in both models. Specifically, neither the Perceived Usefulness × Institutional Readiness interaction [($\beta = -0.087$, $p = .420$)] nor the Perceived Ease of Use × Institutional Readiness interaction [($\beta = 0.095$, $p = .477$)] predicted faculty integration of dark data. These findings underscore that even when accounting for institutional tools, training, and leadership, the traditional TAM variables do not gain predictive strength. The implication is that technical and structural readiness alone does not amplify faculty engagement with complex data practices, a finding that may reflect the invisible and less intuitive nature of dark data within LMS environments.

This outcome aligns with Venkatesh et al.'s (2003) development of the Unified Theory of Acceptance and Use of Technology (UTAUT), which extended TAM by incorporating constructs such as facilitating conditions and social influence. Their findings highlighted the importance of contextual, social, and organizational factors, especially for technologies that are not readily visible or easily interpretable, such as LMS behavioral traces. Similarly, Tsai et al. (2019) noted that faculty engagement with learning analytics is often shaped more by institutional culture and leadership than by individual-level perceptions. In their study, the absence of a data-informed culture and clear policy frameworks inhibited faculty adoption, even when the technical tools were readily available.

In line with these findings, Ifenthaler and Yau (2020) reported that digital self-efficacy and attitudinal readiness were stronger predictors of analytics use than TAM variables. Their international survey emphasized that confidence, professional identity, and previous exposure to analytics tools determined whether faculty used data meaningfully in teaching. These results suggest that future frameworks should incorporate constructs related to psychological readiness and identity, rather than rely exclusively on perceptions of usefulness and usability. This recommendation is reinforced by Ali, Wang, and Johnson (2021), who argue that behavioral intention and digital capacity are superior predictors of system use in online learning environments, and that institutions should shift from interface upgrades to more targeted faculty development.

Additionally, Viberg et al. (2018) emphasized the role of ethics, transparency, and departmental norms in shaping faculty decisions to adopt learning analytics. Their work suggests that without institutional messaging on the value and responsible use of behavioral data, faculty may perceive such tools as either irrelevant or potentially harmful, especially if dark data use feels intrusive or unregulated. These findings mirror the current study's conclusion: dark data use is not simply a matter of technical access or ease of use, but of pedagogical alignment, ethical clarity, and cultural readiness.

Explanation for the Non-Significant Results: A Logical and Theoretical Rationale

The finding that perceived usefulness, perceived ease of use, and institutional readiness did not significantly predict the integration of LMS-generated dark data into instructional design suggests a key limitation in the applicability of traditional adoption models such as the Technology Acceptance Model (TAM) (Davis, 1989) when dealing with emerging, complex technologies like dark data analytics.

TAM has historically been effective in explaining the adoption of well-defined, visible, and user-facing technologies. For example, tools such as learning management systems, virtual classrooms, or gradebooks have clear utility and ease-of-use implications, which align with faculty perceptions and usage intentions (Venkatesh et al., 2003). However, LMS dark data differs from these systems in both visibility and interpretability. It is largely unstructured, often not surfaced by default in LMS dashboards, and requires advanced literacy in data analytics to be meaningful (Ifenthaler & Yau, 2020). As a result, faculty may not be in a position to form coherent judgments of its usefulness or usability, undermining the basic premises of TAM in this context. A relationship mapping of variables as shown in figure 3 reveals weak relationships as indicated by the dotted lines.

Further, the non-significant moderation effects of institutional readiness may indicate that structural support alone is insufficient. Studies by Tsai et al. (2019) and Viberg et al. (2018) emphasize that institutional readiness must go beyond infrastructure and include a culture of data use, ethical clarity, and leadership modeling to influence actual behavioral change. In other words, faculty may have access to tools and training (i.e., readiness), but still lack the confidence, motivation, or cultural incentives to engage with dark data, which is often viewed as ambiguous, time-consuming, or beyond their pedagogical responsibilities.

Moreover, self-efficacy, professional identity, and behavioral intention, variables not tested in this study, have been found to exert stronger influence on complex technology use. For instance, Ifenthaler and Schumacher (2016) found that instructors with high digital confidence were more likely to engage in sophisticated data interpretation tasks, regardless of institutional support. Similarly, Ali, Wang, and Johnson (2021) identified digital readiness and intentionality as better predictors of system use than TAM constructs in online learning environments.

Lastly, it is worth considering that the nature of dark data itself may limit faculty's ability to conceptualize its role in instructional design. As Brooker and Corrin (2023) note, LMS systems rarely present behavioral data in pedagogically meaningful ways. Instead, insights are often buried in clickstream logs, time-on-task metadata, or sentiment-laden forum threads, formats that require not just interest, but analytic competence, and curricular integration strategies to interpret effectively.

In sum, these results do not discredit the usefulness of TAM or institutional readiness frameworks but highlight their limitations when applied to less tangible and cognitively demanding innovations such as LMS dark data. Future studies should consider incorporating additional constructs like digital self-efficacy, data literacy, institutional data culture, and behavioral intentions to develop more robust models that explain faculty engagement with next-generation educational data sources. This study contributes to a growing scholarly consensus that faculty integration of innovative educational technologies, especially those involving complex, non-visible data, requires a multidimensional framework. Models that combine TAM or UTAUT with organizational learning, digital self-efficacy, and data culture theory will be better suited to explain and influence the instructional use of LMS dark data. Future research should explore these factors empirically and consider mixed-method or longitudinal designs to capture how data fluency and institutional priorities evolve over time.

VI. CONCLUSION

This study investigated the extent to which perceived usefulness, perceived ease of use, and institutional readiness predict faculty integration of LMS-generated dark data into instructional design. Despite the established relevance of the Technology Acceptance Model (TAM) in technology adoption research, the findings revealed no statistically significant relationships between these constructs and the use of dark data by faculty. These results suggest that traditional acceptance frameworks may not adequately capture the complex behaviors and contextual factors associated with the adoption of unstructured and behavioral data in educational settings.

The study contributes to the growing body of literature that urges a reexamination of simplistic adoption models in favor of more comprehensive frameworks that account for organizational culture, faculty self-efficacy, behavioral intentions, and data literacy ecosystems. It also highlights the need for institutions to go beyond tool provision and cultivate a culture of data-informed teaching, where faculty are equipped, encouraged, and empowered to leverage hidden insights within LMS platforms.

Future research should explore these additional dimensions and their interactions with technological and institutional variables, using both quantitative and qualitative methods. As the educational landscape becomes increasingly data-rich, unlocking the potential of dark data will require not only robust systems and frameworks but also a transformation in how educators view and value their role in shaping evidence-based, adaptive learning environments.

Implications for Practice and Policy

The findings of this study carry important implications for both institutional leaders and instructional designers aiming to foster data-informed teaching practices. First, the weak predictive power of TAM constructs suggests that interventions focused solely on improving user perceptions of usefulness or ease of use may be insufficient. Instead, institutions should consider holistic strategies that include professional development, ongoing mentoring, and faculty learning communities focused on data fluency and practical application of behavioral LMS data.

Second, while institutional readiness did not significantly predict dark data integration in this study, this may reflect the gap between technical provision and cultural adoption. Training programs should go beyond introducing tools to cultivating a culture of inquiry and evidence-based decision-making, where instructors are empowered to explore and act on behavioral data insights. Leadership plays a vital role in modeling this culture and embedding it into performance expectations, teaching evaluations, and instructional design workflows.

From a policy standpoint, transparent communication about data ethics, access protocols, and learner privacy is essential to reduce faculty resistance and confusion regarding the use of behavioral data. Institutional analytics frameworks must clearly define what constitutes "dark data," how it can be responsibly interpreted, and how it aligns with teaching and learning outcomes.

Limitations

Despite its contributions, this study has several limitations. First, the use of self-reported survey data may be subject to social desirability bias or inconsistencies in how respondents interpret key terms such as "dark data." Although efforts were made to define variables clearly, future research may benefit from incorporating objective usage metrics or learning analytics dashboards to triangulate reported behaviors.

Second, the sample, while diverse in terms of field and faculty type, was limited to institutions using specific LMS platforms (Canvas, Blackboard, Moodle). This may affect generalizability, especially for institutions that rely on proprietary or open-source LMS tools with different data architectures or faculty analytics access.

Third, while regression analysis tested direct effects of TAM constructs and readiness, the study did not explore potential mediators (e.g., behavioral intention, digital self-efficacy) or moderators (e.g., teaching modality, academic discipline) that could influence these relationships. Incorporating such variables in future research may offer a more nuanced understanding of the mechanisms behind dark data integration.

Recommendations for Future Research

Given the limited explanatory power of TAM constructs found here, future research should explore expanded theoretical models that integrate UTAUT (Venkatesh et al., 2003), digital self-efficacy (Ifenthaler & Yau, 2020), and organizational data culture (Tsai et al., 2019; Viberg et al., 2018). These models can help better capture the behavioral and institutional complexity involved in adopting unstructured LMS data for instructional purposes.

Qualitative studies involving case analyses, faculty narratives, or ethnographic approaches could also shed light on contextual barriers and affordances that quantitative methods may overlook. Specifically, exploring the interplay between departmental expectations, data literacy, and institutional incentives could illuminate the conditions under which dark data becomes a practical resource rather than a missed opportunity.

Finally, research should examine student perspectives on the use of behavioral data in course adaptation. Understanding how learners perceive and respond to data-driven instructional changes could enhance the ethical and pedagogical robustness of future data integration initiatives.

REFERENCES

[1] Ali, L., Wang, H., & Johnson, N. A. (2021). Technology acceptance in online learning: A meta-analytic review. *Computers & Education, 173*, 104271. https://doi.org/10.1016/j.compedu.2021.104271

[2] Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, *3*(2), 77–101.

[3] Brooker, A., & Corrin, L. (2023). *Rethinking engagement metrics: Leveraging dark data in LMS for deeper learning insights*. Journal of Learning Analytics, 10(1), 44–62. https://doi.org/10.18608/jla.2023.7739

[4] Creswell, J. W., & Plano Clark, V. L. (2018). *Designing and conducting mixed methods research* (3rd ed.). SAGE.

[5] Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340. https://doi.org/10.2307/249008

[6] Fan, S., & Zhang, D. (2020). Dark data: Challenges and opportunities. *Big Data Research*, 19, 100153. https://doi.org/10.1016/j.bdr.2019.100153

[7] Gkontzis, A., Kotsiantis, S., & Panagiotakopoulos, C. (2022). Predicting student performance in Moodle LMS using machine learning techniques and behavioral data. *Education and Information Technologies*, 27, 875–893. https://doi.org/10.1007/s10639-021-10657-2

[8] Ifenthaler, D., Mah, DK., Yau, J.YK. (2019). Utilising Learning Analytics for Study Success: Reflections on Current Empirical Findings. In: Ifenthaler, D., Mah, DK., Yau, J.YK. (eds) Utilizing Learning Analytics to Support Study Success. Springer, Cham. https://doi.org/10.1007/978-3-319-64792-0_2

[9] Ifenthaler, D., & Yau, J. Y.-K. (2020). Utilizing learning analytics to support study success in higher education: A systematic review. *Educational Technology Research and Development, 68*, 1961–1990. https://doi.org/10.1007/s11423-020-09788-z

[10] Siemens, G. (2013). Learning analytics: The emergence of a discipline. *American Behavioral Scientist, 57*(10), 1380–1400. https://doi.org/10.1177/0002764213498851

[11] Tsai, Y. S., Poquet, O., Gašević, D., Dawson, S., & Pardo, A. (2019). Complexity leadership in learning analytics: Drivers, challenges and opportunities. *British Journal of Educational Technology, 50*(6), 2839–2854. https://doi.org/10.1111/bjet.12846

[12] Tsai, Y.-S., et al. (2020). Complexity leadership in learning analytics: Drivers, challenges and opportunities. *British Journal of Educational Technology*, *51*(4), 1075–1090.

[13] Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478. https://doi.org/10.2307/30036540

[14] Viberg, O., et al. (2018). The current landscape of learning analytics in higher education. *Computers in Human Behavior*, *89*, 98–110.

[15] Viberg, O., Hatakka, M., Bälter, O., & Mavroudi, A. (2018). The current landscape of learning analytics in higher education. *Computers in Human Behavior, 89*, 98–110. https://doi.org/10.1016/j.chb.2018.07.027