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Managing Attrition in Open and Distance Learning: Learner Insights for Information-Driven Retention Strategies

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ABSTRACT

Open and Distance Learning (ODL) provides flexible, accessible, and cost-effective education, yet student attrition remains a persistent challenge with significant implications for learners and institutions. This study explores the key factors contributing to dropout among former students at Universiti Teknologi MARA (UiTM) through semi-structured interviews with 15 participants. Thematic analysis revealed eight major contributors: self-regulation, personal circumstances, teaching quality, environmental factors, emotional pressures, financial barriers, communication challenges, and technological constraints. Findings underscore the interplay between individual, institutional, and structural factors shaping persistence in ODL. Building on an information management perspective, the study proposes targeted strategies, including structured learning analytics, adaptive scheduling, enhanced teaching quality, and socio-technical support mechanisms. By integrating technological, pedagogical, and student-support dimensions, these interventions offer a holistic framework to improve retention, reduce attrition, and foster equitable and sustainable ODL ecosystems.

INTRODUCTION

Open and Distance Learning (ODL) offers an alternative mode of education that enables learners to study at their preferred pace, location, and schedule, without the constraints of a traditional classroom setting. By integrating various media and technological tools, ODL delivers learning materials and supports interaction between students, instructors, and learning resources (Gaskell, 2017). This approach provides multiple advantages, including flexibility, accessibility, cost-effectiveness, convenience, and opportunities for personalized learning. While ODL provides a flexible educational model that enables students to access learning opportunities anytime and anywhere via the internet. This format requires learners to take personal responsibility and exercise considerable autonomy, managing their own study schedules and learning decisions to achieve course objectives. Consequently, universities and colleges strive to cultivate a supportive learning environment that empowers students to succeed and complete their studies (Kamaruddin et al., 2024).

Student attrition has long been recognized as a critical issue in higher education, and it poses heightened challenges in Open and Distance Learning (ODL) environments. Despite institutional efforts to enhance learner support, a significant number of students continue to withdraw from their studies before completion. Attrition, defined as the likelihood of students discontinuing their academic programs prematurely, has far-reaching implications. On an individual level, non-completion can hinder socio-economic advancement, limit career opportunities, and negatively affect personal development. For institutions, high dropout rates result in financial losses, underutilization of resources, and reputational damage, particularly when retention rates are linked to funding and performance indicators (Trusty et al., 2025). As such, the study emphasizes the importance of identifying the underlying factors contributing to dropout in ODL contexts to inform the development of targeted and evidence-based interventions. Understanding these factors is essential for improving student retention, satisfaction, and overall academic success (Rahmani et al., 2024).

Therefore, an in-depth exploration of the fundamental drivers of student attrition in higher education remains a matter of critical importance in Malaysia. Such research offers valuable insights to help both learners and institutions mitigate the negative consequences of dropout. By identifying key drivers of ODL student withdrawal and developing a contextualized intervention model for UiTM, this study aims to contribute meaningfully to reducing attrition and strengthening educational outcomes in Malaysia's evolving higher education landscape. Thus, the objectives for this study which are: (i) to explore the key factors contributing to student attrition in Open and Distance Learning (ODL) at Universiti Teknologi MARA (UiTM), and (ii) to propose strategies informed by information management principles aimed at enhancing student engagement, motivation, and institutional support to reduce attrition and promote long-term success in ODL environments.

LITERATURE REVIEW

Over the past decades, student attrition has remained a persistent concern in Malaysia's higher education landscape, with numerous studies underscoring its multifaceted nature. Socio-economic disparities, such as variations in family income and parental education, alongside academic challenges including limited self-regulation, inadequate foundational knowledge, and underdeveloped study skills, have been repeatedly linked to increased dropout risk (Rahman et al., 2025). Personal struggles such as low self-esteem, social isolation, and geographical barriers, further compound these challenges, as do institutional and environmental factors highlighted in established attrition frameworks (Had Sabtu et al., 2016; Zhidkikh et al., 2025).

In the context of ODL attrition is shaped by a complex interplay of technological, financial, environmental, personal, self-regulatory, communicative, and emotional determinants. Technological barriers including inadequate connectivity, limited device access, low digital literacy, and poorly designed course materials continue to hinder participation, particularly among students from disadvantaged backgrounds (Gonzales et al., 2018; Vogels, 2021). Financial constraints, unstable study environments, and competing work–study demands further erode learner persistence (Aguilera-Hermida, 2020; UNESCO, 2023). In addition, personal factors such as motivation, self-efficacy, and time management play a critical role in sustaining engagement, while deficits in self-regulated learning (SRL) skills significantly increase withdrawal likelihood (Broadbent & Fuller-Tyszkiewicz, 2018; Li & Zhang, 2024). Communication quality and emotional well-being are equally vital, as meaningful interaction fosters social presence and belonging, whereas isolation and inadequate support accelerate disengagement (Bağrıacık Yılmaz & Karataş, 2022; García-Morales et al., 2024).

Addressing these challenges requires not only pedagogical and institutional reforms but also robust information management approaches. By systematically collecting, integrating, and analysing learner data, institutions can identify early warning signs and design proactive interventions. Learning analytics platforms can track participation trends, generate alerts for at-risk learners, and support personalised feedback. Centralised knowledge repositories, AI-driven support tools, and digital resource mapping can improve academic assistance and access to physical learning spaces. Furthermore, integrated communication systems can monitor and enhance interaction quality, while asset management platforms facilitate equitable device allocation. Such data-driven strategies strengthen institutional capacity to address self-regulation deficits, technological inequities, and emotional isolation, ultimately fostering inclusive, connected, and sustainable ODL participation (Shen et al., 2024).

METHODOLOGY

Data Collection

This study employed a semi-structured interview method to collect qualitative data from 15 former full-time students of Universiti Teknologi MARA (UiTM) who had withdrawn from their studies. Data collection took place between August and November 2023, with interviews scheduled according to participants' availability. All interviews were conducted via video conferencing platforms, such as Google Meet or Zoom, depending on individual preference. Particularly, participants were purposively selected based on their availability and willingness to share their experiences, representing a diverse range of programmes, disciplines, and levels of study. Purposive sampling is a non-probability sampling technique that involves selecting participants based on specific criteria that are relevant to the research question or study objectives. It is often used in qualitative research where the goal is to gain in-depth insights into a particular phenomenon or population. One example of a definition of purposive sampling is provided by Polit and Beck (2018), who state that purposive sampling "involves selecting individuals or groups who meet predetermined criteria to participate in a study" (p. 242).

A semi-structured interview guide was developed for the study, which included open-ended questions and prompts to explore the participants' reasons for dropping out, experiences during their online studies at home, and their perceptions of the factors that contributed to their decision to discontinue their studies. The interview guide was designed to allow for flexibility and in-depth exploration of the research topic. Interviews lasted between 30 minutes and 90 minutes, depending on the depth of participant engagement. Prior to participation, all individuals were provided with detailed information outlining the background, purpose, and scope of the research. Informed consent was obtained from each participant. Interviews were audio-recorded with permission, and supplementary field notes were taken to capture additional observations. The recordings were subsequently transcribed verbatim, and thematic analysis was applied to identify patterns and themes relevant to the research objectives.

The study was conducted in full compliance with established ethical protocols for research involving human participants. Participants were informed of their right to withdraw from the study at any stage without penalty, and strict measures were implemented to ensure confidentiality and privacy. Personal information was securely stored, with access restricted to authorised personnel only. Anonymity was maintained through the use of pseudonyms or unique participant codes in all transcripts, analyses, and publications. Ethical approval for the study was granted by the Universiti Teknologi MARA (UiTM) Ethics Review Board following a comprehensive review of the research design, consent procedures, and data management strategies. This approval affirmed that the study met high ethical standards, ensuring that participants' rights, dignity, and well-being were safeguarded throughout the research process.

Data Analysis

For this study, qualitative data were analysed using NVivo 12 software to facilitate a reflexive thematic analysis. The analysis followed Braun and Clarke's (2006) six-phase framework, which offers a systematic approach to identifying, analysing, and reporting patterns within qualitative data, thereby enabling a deeper understanding of participants' experiences, perspectives, and beliefs. The process began with data familiarisation, involving repeated reading of transcripts, note-taking, and immersion in the material to gain a comprehensive overview.

Subsequently, initial codes were generated through line-by-line coding, capturing meaningful features of the data. These codes were then organised into potential themes by clustering related concepts into broader categories and identifying relevant subthemes. In the next phase, themes were reviewed and refined to ensure coherence, internal consistency, and accurate representation of the dataset. This iterative process involved critical reflection and discussion to enhance analytic rigour. Finally, the themes were clearly defined, named, and integrated into the final report, ensuring that the analysis provided a coherent and insightful account of the data. Braun and Clarke's model, thus offered a structured yet flexible method to derive meaningful interpretations from qualitative evidence.

STUDY FINDINGS

The findings presented are derived from the researchers' analysis of data collected from 15 respondents. The participants were drawn from a diverse range of faculties, including two participants from the Faculty of Communication and Media Studies, Faculty of Information Management, Faculty of Business and Management, Faculty of Sports Management, Faculty of Education, and Faculty of Law. Additionally, one respondent from each of the following faculties: the Faculty of Art and Design, Faculty of Health Sciences, and Faculty of Medicine. Following the completion of the interviews, the data obtained from the 15 respondents were organised in a table (see Table 1), ranking the reported factors contributing to student attrition in descending order of frequency.

Table 1: Factors contributing to dropout in ODL setting.

Factors	Times referenced	Percentage
Self-Regulation	59	23.0%
Personal	53	20.7%
Teaching Quality	41	16.0%
Environmental	38	14.8%
Emotional	21	8.2%
Financial	20	7.8%
Communication	13	5.1%
Technological	11	4.3%

Notably, the finding of this study identified eight key factors contributing to dropout in the ODL setting. In essence, self-regulation was the most frequently cited factor, accounting for 23.0% of responses. This was followed closely by personal factors (20.7%) and teaching quality (16.0%). Environmental influences represented 14.8%, while emotional (8.2%) and financial challenges (7.8%) were cited less frequently. The least reported factors were communication issues (5.1%) and technological barriers (4.3%). Collectively, these findings suggest that internal learner attributes and personal circumstances play a more substantial role in dropout than external or structural factors. Furthermore, each factor was further categorised into specific subtopics to provide greater analytical clarity as follows:

Self-Regulation Factor

Self-regulation emerged as a central determinant of attrition in the ODL context, with multiple dimensions shaping students' withdrawal decisions. Ineffective time management was a prominent challenge, as many participants struggled to structure their schedules and prioritise academic tasks. The flexible nature of ODL, while offering autonomy, was perceived to erode discipline in allocating study hours, meeting deadlines, and sustaining consistent learning routines. One student reflected that "most of the time it is last minute" [Respondent 05], while another described a recurring tendency to work intensively just before deadlines: "The due date is close… finally at that time just did everything" [Respondent 01].

Reduced concentration further hindered learning. Home-based distractions ranging from background noise and family interactions to frequent mobile phone use were widely reported as barriers to focus. As one participant estimated, their concentration during online classes was "50%" [Respondent 02], while another admitted, "My attention is all over the place… mostly it's my phone" [Respondent 05]. Such interruptions disrupted engagement with course content, impeded comprehension, and weakened knowledge retention.

Inadequate revision practices compounded these issues. Several students acknowledged that they engaged with course materials only in the lead-up to assessments. "I only study when there's an upcoming test" [Respondent 02], one participant confessed, while another stated simply, "So far, none" [Respondent 14] when asked about pre-reading new topics. These gaps limited knowledge consolidation, undermined academic confidence, and ultimately contributed to attrition.

Personal Factor

Personal circumstances also played a significant role in shaping withdrawal decisions, particularly through adaptation challenges, competing family and work demands, and declining motivation. Family obligations including childcare, household responsibilities, and caregiving duties often diverted time and energy away from studies. One student explained, "As a daughter… I have a duty at home… to take care of my siblings… sometimes things around the house can distract me from online studies" [Respondent 03], while another described the delicate balance between both spheres: "They [family] don't bother me as much, as long as I can manage between my schoolwork and my house chores" [Respondent 13].

Employment commitments introduced further constraints, with part-time or full-time work leading to fatigue and reduced study time. "I miss my class… because I am working part-time" [Respondent 04], one respondent reported, while another admitted, "I can't focus too much time on assignments… due to time and work constraints" [Respondent 07].

Declining academic interest, often tied to reduced motivation and limited social interaction, was also evident. One participant shared, "After that, I didn't feel like studying, my mood was lost" [Respondent 15], while another reflected, "Throughout year 1, I didn't study much… so I didn't even try to learn" [Respondent 12].

Teaching Quality Factor

The perceived quality of teaching significantly influenced students' persistence in ODL. Many participants cited a reliance on less interactive communication channels, which constrained opportunities for dialogue and timely clarification. As one student noted, lecturers would often "send slides [on Telegram]… then voice over it, then we listen to explanations bit by bit" [Respondent 01]. In some cases, live sessions were replaced with "a replacement class or a recorded lecture" [Respondent 04], further reducing real-time engagement.

The absence of timely, constructive feedback was another concern. Delayed responses to queries, described by one student as "usually… slow, it's not fast" [Respondent 01], hindered students' ability to address uncertainties, monitor progress, and stay motivated. Unengaging teaching styles such as reading directly from slides without elaboration further diminished interest and weakened the learning experience, leading some students to disengage.

Environmental Factor

Environmental conditions, particularly connectivity limitations and local distractions, posed significant barriers to retention. Students in rural or remote areas often faced unstable internet access, which disrupted attendance, delayed access to materials, and interfered with assessments.

One participant described resorting to "drive a car [and] sit in the car to find an Internet connection" [Respondent 11], while another recounted being disconnected mid-test and forced to "submit my test… by typing it into my phone instead of my laptop" [Respondent 13].

Environmental distractions also reduced study effectiveness. Noise from renovations, household interruptions, and shared living spaces often disrupted concentration. As one student observed, "My neighbour was renovating their house… during presentations, there's noise from lorries" [Respondent 02], while another noted, "I'm focusing in class and somebody comes… I have to open the door… whether you want it or not" [Respondent 04].

Emotional Factor

Emotional pressures comprising stress, anxiety, and feelings of isolation were strongly associated with attrition. Many students described heightened stress in adjusting to ODL, citing heavier workloads, technological challenges, and limited support. One participant stated, "It's stressful… because there's no peer support" [Respondent 12], while another reflected, "I think I have more mental breakdowns during ODL instead of physical class" [Respondent 13].

Feelings of isolation further eroded engagement. The lack of face-to-face contact limited opportunities for collaboration and belonging. As one student explained, "If we had an assignment, we just created a WhatsApp group and divide the work" [Respondent 15], while another lamented the absence of basic peer familiarity: "So, how am I going to know whose phone number is whose" [Respondent 11].

Financial Factor

Financial constraints, including the cost of devices and learning materials, were major barriers to retention. Many students reported significant expenses in acquiring essential digital tools, with one explaining, "I had to buy a new one… it's a necessity… and if you want… more tools such as a tripod… you have to record a lot of videos for presentation" [Respondent 04]. Another added, "I had to get a new microphone during ODL… basic things like keyboards and then mouse" [Respondent 13].

The cost of course-specific materials also posed challenges, particularly for students in resource-intensive fields. A law student reported spending "almost RM300 on textbooks and act books" each semester [Respondent 02], while a fine arts student noted that high material costs "affects my grade because my course… costs a lot of money" [Respondent 03].

Communication Factor

Communication barriers both with lecturers and peers emerged as a critical factor in withdrawal decisions. Limited lecturer availability and slow responses hindered timely clarification. "We don't meet the lecturer face-to-face; I can't ask questions directly" [Respondent 14], one student explained, while another highlighted technical issues: "Even lecturers… have internet connection problems during heavy weather" [Respondent 02].

Peer collaboration was also problematic. Group assignments were sometimes undermined by unequal participation, as one respondent described: "Friends [who] are a back seat rider of my assignment" [Respondent 04]. Informal communication channels were not always effective; "When we discuss in WhatsApp, there is a lot of complications" [Respondent 01], one participant reported, while another noted that "connection issues… are unavoidable" [Respondent 13].

Technological Factor

Finally, technological limitations particularly inadequate hardware were a substantial barrier to retention. Many students lacked access to suitable devices or peripherals, restricting participation in online classes and reducing interaction quality. One student recounted, "I had an old laptop… a hand-me-down… almost eight, six years old… it is a torture to use that laptop, to say the least" [Respondent 05]. These technological gaps left learners feeling disadvantaged, frustrated, and demotivated, increasing the likelihood of withdrawal.

DISCUSSIONS

The findings of this study underscore the centrality of self-regulation as the most influential factor contributing to dropout in the ODL setting (23.0%). Consistent with previous literature, the autonomy inherent in distance learning requires learners to exercise effective time management, sustained concentration, and consistent revision habits, which refer to the skills that many participants admitted struggling with. Prior research in learning analytics highlights that self-regulation patterns can be traced through engagement data, such as login frequency, assessment submissions, and participation in online discussions (Papamitsiou & Economides, 2014). These findings also align with Lee and Choi (2011), who argue that individual learner characteristics, including self-regulatory abilities are among the most significant predictors of online course completion. As suggested by Ifenthaler and Yau (2020), embedding analytics-informed early warning systems and providing targeted support can help ODL providers scaffold learner self-regulation and reduce dropout rates.

Beyond individual learning habits, personal and teaching quality factors emerged as the next most significant contributors to dropout, accounting for 20.7% and 16.0% respectively. Personal demands including family obligations, work responsibilities, and declining motivation illustrate the tension between learners' academic and non-academic roles. Such challenges mirror findings by Park and Choi (2009), who emphasized that external support from family and employers is critical for persistence in online learning. Meanwhile, the perceived quality of teaching, particularly lecturer responsiveness and feedback, influenced students' engagement and motivation. Prior work shows that weak instructional design and limited interaction are frequently associated with dropout in online learning contexts (Lee, Choi, & Kim, 2013). Learning analytics can provide additional insights into these patterns by identifying low-engagement teaching practices and mapping how delays in feedback correlate with student disengagement (Tempelaar, Rienties, & Giesbers, 2015). Thus, dropout is not merely an individual challenge but also one shaped by institutional teaching practices.

External and structural barriers, while less frequently cited, were not insignificant. Environmental factors (14.8%), emotional pressures (8.2%), financial constraints (7.8%), communication barriers (5.1%), and technological challenges (4.3%) collectively reveal how contextual conditions intersect with learner experiences. The accounts of unstable internet, lack of suitable devices, feelings of isolation, and the cost of learning resources confirm findings by Kemp (2002) and Elibol and Bozkurt (2023), who highlight that environmental and structural barriers remain persistent risks for retention in distance education. Moreover, dropout should not be understood as an individual failure but rather as a systemic outcome influenced by unequal access, emotional burdens, and financial pressures (Shaikh et al., 2022). Learning analytics has the potential to extend beyond academic behaviors to monitor these risks, for example by detecting inactivity, disengagement, or patterns of assessment non-submission (Siemens & Long, 2011). Taken together, this study reinforces the need for a holistic retention strategy, where ODL institutions not only promote learner self-regulation but also enhance teaching quality, provide socio-economic and technological support, and build more inclusive online learning environments.

Addressing these eight key factors collectively provides a holistic approach to fostering persistence in ODL. By integrating the findings from this study with existing literature and sector best practices, a comprehensive model has been developed that serves not only as a diagnostic tool but also as an actionable framework to enhance retention, promote inclusivity, and ensure continuous improvement in ODL practice. However, identifying these factors alone is insufficient, the effective intervention requires translating these insights into structured, evidence-based strategies.

Information Management–Driven Strategies for Mitigating Attrition in ODL

To overcome the dropout factors, this study offers targeted strategies grounded in an information management perspective. This approach emphasises the strategic collection, organisation, dissemination, and use of learning-related information to support decision-making, optimise resource allocation, and personalise learner support. Information management–driven interventions ensure that academic, technological, and socio-emotional dimensions of ODL are addressed in a coordinated and systematic manner, thereby enabling timely responses to emerging risks.

Table 2: Information Management–Driven Strategies for Mitigating Attrition in ODL

Mitigation Strategy	Supporting Literature
Enhancing self-regulation through structured learning analytics	Learning analytics enables early detection of at-risk learners and supports targeted intervention (Long & Siemens, 2011; Hlosta et al., 2022).
Supporting personal circumstances via flexible, data-driven scheduling	Adaptive education designs improve engagement in flexible learning environments (El-Sabagh, 2021).
Improving teaching quality through feedback loops and content enhancement	Instructor presence and timely feedback improve retention (Hachey et al., 2023).
Minimising environmental disruptions with offline learning packages	Inclusive educational delivery in low-bandwidth contexts improves access (World Bank, 2021).
Addressing emotional well-being through digital peer networks	AI chatbots and digital peer networks reduce ODL attrition (Ndunagu et al., 2025).

Reducing financial barriers with OER adoption	OER adoption lowers financial barriers and increases equity (Wiley et al., 2017).
Strengthening communication channels via unified platforms	Centralised communication reduces fragmentation and improves engagement (Hrastinski, 2008).
Upgrading technological infrastructure with device support	Equitable access to hardware enhances participation in ODL (Moore & Kearsley, 2012).

Building on the identified factors contributing to attrition, it is essential to implement targeted strategies that address these challenges holistically. Table 2 outlines the proposed mitigation measures, which draw upon an integrated information management approach combining technological, pedagogical, and student-support dimensions. Such an approach recognises that persistence in ODL depends not only on academic readiness but also on the effective organisation, delivery, and monitoring of learning-related processes. Structured learning analytics embedded within learning management systems can track progress, issue automated reminders, and alert instructors when students are at risk, enabling timely interventions that strengthen time management and task prioritisation (Long & Siemens, 2011; Hlosta et al., 2022). Flexible, data-driven scheduling supported by predictive modelling allows personalised learning pathways that accommodate diverse commitments, thereby enhancing engagement (El-Sabagh, 2021). Teaching quality remains pivotal, with structured feedback loops, real-time academic support, and multimedia-rich content fostering instructor presence and timely feedback, both linked to improved retention (Hachey et al., 2023).

From an infrastructural perspective, inclusive delivery in low-bandwidth contexts through offline learning packages and compressed content expands access for students in connectivity-constrained areas (World Bank, 2021). Emotional well-being can be bolstered via digital peer networks and AI-driven support channels, mitigating feelings of isolation that contribute to dropout (Ndunagu et al., 2025). Financial barriers may be reduced through open educational resources (OERs), which lower costs and promote equitable access (Wiley et al., 2017). In parallel, centralised communication platforms consolidate announcements, discussions, and feedback to reduce fragmentation and strengthen engagement (Hrastinski, 2008). Finally, equitable hardware provision through device-loan schemes and procurement partnerships can enhance participation for economically disadvantaged learners (Moore & Kearsley, 2012). When embedded within an institution-wide information management framework, these measures allow for systematic monitoring, targeted intervention, and continuous improvement ultimately fostering a more equitable, sustainable, and engagement-focused ODL ecosystem.

Effectively reducing attrition in ODL hinges on a coordinated approach that blends technology, pedagogy, and targeted student support. By enabling timely interventions, personalized learning pathways, and inclusive access, institutions can strengthen engagement and persistence. When embedded within a comprehensive information management framework, these strategies transform ODL into a more equitable, resilient, and student-centered learning environment.

LIMITATIONS AND FUTURE STUDY

This study has several limitations that warrant consideration. The sample was primarily drawn from students at the Universiti Teknologi MARA (UiTM) Selangor Branch, which may limit the generalizability of the findings to other higher education institutions with differing contexts. Moreover, the relatively small and diverse sample, spanning multiple faculties, may affect the representativeness of the results. As a qualitative study, the findings rely on self-reported experiences, which may be subject to recall bias or personal interpretation, and the cross-sectional design limits the ability to infer causality or track changes in attrition factors over time. Contextual influences such as institutional policies, socio-economic conditions, and technological infrastructure were not exhaustively examined, potentially affecting transferability to other ODL settings.

Future research could address these limitations by incorporating larger, multi-institutional samples, employing longitudinal designs, and integrating quantitative metrics such as learning analytics to triangulate self-reported data. Additionally, exploring broader contextual factors would provide a more comprehensive understanding of attrition dynamics in diverse ODL environments. From a knowledge management perspective, such approaches can generate institutional knowledge assets that systematically document, analyse, and share insights on student behavior, enabling universities to build evidence-based repositories for decision-making. By situating dropout research within knowledge management frameworks, future studies can contribute not only to academic theory but also to institutional practices that sustain retention and persistence in ODL.

CONCLUSION

Overall, this study has highlighted self-regulation as the most critical determinant of dropout in the ODL context, supported by personal circumstances and teaching quality, with environmental, emotional, financial, communication, and technological challenges further shaping learners' persistence. These findings reaffirm that attrition is not the result of a single deficit but rather a complex interplay between individual agency, institutional practices, and structural conditions. By integrating the insights of learning analytics with an information management perspective, this study underscores the value of systematically collecting, organising, and applying learner-related data to inform institutional decision-making. Rather than viewing dropout as an individual failure, ODL providers can leverage analytics-informed interventions and structured knowledge management processes to build inclusive, evidence-driven retention strategies. The proposed information management–driven strategies offers actionable pathways for enhancing self-regulation, supporting personal commitments, improving teaching quality, reducing barriers to access, and strengthening communication and infrastructure. Theoretically, the study contributes to the literature on dropout, persistence, and retention in ODL by extending the discussion beyond learner characteristics to a holistic model that embeds institutional knowledge creation and use. Practically, it provides a framework that ODL institutions can adapt to reduce attrition and promote sustainable participation. Moving forward, embedding such strategies into institutional practice has the potential to transform ODL into a more equitable, resilient, and student-centered educational ecosystem.

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