Journal of Informatics Education and Research
ISSN: 1526-4726
Vol 6 Issue 3 (2026)

A Study on Learner Analytics in Self-Regulated Learning for Working Professionals on Digital Platforms in Nashik District, Maharashtra

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Abstract

Self-regulated learning (SRL) has emerged as a critical competency for working professionals engaged in continuous education through digital platforms. As online learning proliferates in India, understanding how learner analytics (LA) can support and enhance SRL processes be-comes increasingly important for both platform designers and educators. This study investigates the relationship between learner analytics features and self-regulated learning behaviours among 200 working professionals enrolled in digital learning courses in Nashik District, Maharashtra. Employing a mixed-methods research design, the study combines quantitative survey data mea-sured on established SRL scales with qualitative insights from semi-structured interviews and platform log data analysis. Findings reveal that 67.5% of respondents demonstrate moderate to high SRL engagement, with goal setting (60%) and self-monitoring (65%) being the most fre-quently adopted strategies. However, only 38% regularly utilise learning analytics dashboards, and merely 35% adjust their study strategies based on analytics data. Pearson correlation analysis shows a significant positive relationship between SRL engagement scores and learning outcomes (r = 0.62, p < 0.001), and chi-square tests confirm that awareness of LA features is significantly associated with SRL strategy adoption (χ^2 = 14.83, p < 0.01). The study proposes a Learner Analytics Integration Framework that maps LA features to Zimmerman's three-phase SRL model, offering actionable design recommendations for digital learning platforms targeting working professionals.

Keywords: Learner Analytics, Self-Regulated Learning, Working Professionals, Digital Platforms, Nashik, Online Learning, Zimmerman's SRL Model

1 Introduction

The rapid expansion of digital learning platforms has fundamentally transformed continuing professional development, enabling working adults to acquire new competencies while maintain-ing their employment commitments [20]. In India, the online education market is projected to reach USD 10 billion by 2025 [12], driven by increasing internet penetration, government initia-tives such as SWAYAM and NPTEL, and the growing demand for upskilling in a competitive labour market. Maharashtra, as India's second-most industrialised state, has a substantial pop-ulation of working professionals seeking flexible learning opportunities, with Nashik emerging as an educational hub attracting learners from diverse professional backgrounds [15].

However, the effectiveness of digital learning is significantly influenced by learners' capacity for self-regulation [3]. Self-regulated learning (SRL), defined as the proactive process whereby learners strategically manage their cognition, motivation, and behaviour to achieve academic goals [25], is particularly critical for working professionals who must balance educational pur-suits with professional and personal responsibilities. Research consistently demonstrates that SRL capabilities are among the strongest predictors of academic success in online learning en-vironments [19, 18].

Learner analytics (LA), defined as the measurement, collection, analysis, and reporting of data about learners and their contexts [20], offers a promising mechanism for supporting SRL processes. By providing learners with real-time feedback on their learning behaviours, progress, and performance patterns, LA tools can potentially scaffold the metacognitive processes central to SRL [24, 23]. Despite this potential, empirical evidence on how working professionals in regional Indian contexts engage with both SRL strategies and learner analytics features remains scarce [9].

This study addresses three research questions: (RQ1) What is the nature and extent of SRL strategy adoption among working professionals using digital platforms in Nashik? (RQ2) To what extent are working professionals aware of and utilising learner analytics features? (RQ3) What is the relationship between learner analytics utilisation and self-regulated learning be-haviours? By examining these questions, the research contributes to the growing body of lit-erature on SRL-supported digital learning in emerging economies and offers practical design recommendations for platform developers.

2 Literature Review

2.1 Self-Regulated Learning in Digital Environments

Zimmerman's three-phase cyclical model of SRL [25] remains the most widely adopted theoretical framework for understanding self-regulation in learning contexts. The model delineates three iterative phases: forethought (planning and goal setting), performance (self-control and self-monitoring during learning), and self-reflection (self-evaluation and adaptive responses following learning outcomes). Each phase encompasses both metacognitive and motivational components that interact dynamically to influence learning effectiveness.

In digital learning environments, the application of SRL theory has revealed both opportu-nities and challenges. Broadbent and Poon [3] conducted a meta-analysis of 71 studies examining SRL in online learning, finding that SRL strategies were significantly associated with academic achievement (d = 0.45), with goal setting and time management emerging as the strongest predictors. However, working professionals face unique SRL challenges compared to traditional students, including competing time demands from employment, fragmented study schedules, and reduced access to institutional support structures [11, 21].

Research by Hodges [8] demonstrated that working adult learners in online programmes exhibit distinct SRL profiles, with environmental restructuring and help-seeking strategies play-ing more prominent roles than in traditional student populations. Similarly, Cho and Shen [5] found that self-monitoring behaviours in online courses were significantly predicted by learners' perceptions of the learning management system's feedback capabilities, suggesting that platform design influences SRL enactment.

2.2 Learner Analytics and SRL Scaffolding

Learner analytics has evolved from descriptive dashboards showing basic engagement metrics to predictive models that identify at-risk learners and recommend personalised interventions [20, 7]. The conceptual alignment between LA and SRL is compelling: LA provides the external data infrastructure that can support the internal metacognitive processes central to SRL [24]. Specifically, LA dashboards can support forethought phase activities by helping learners set realistic goals based on historical data, performance phase activities through real-time self-monitoring prompts, and self-reflection phase activities by providing comparative performance analytics [23, 16].

However, empirical evidence on the effectiveness of LA in supporting SRL remains mixed. Jivet et al. [10] found that many learners do not engage deeply with analytics dashboards, often exhibiting superficial interaction patterns. Similarly, Teasley [22] reported that simply providing analytics data without pedagogical scaffolding does not significantly improve learning outcomes. These findings underscore the importance of designing LA features that are not only informative but also actionable and integrated into learners' existing SRL workflows [9].

2.3 The Indian Context and Research Gap

India's digital learning landscape has witnessed explosive growth, catalysed by the National Edu-cation Policy 2020 [17] and platforms such as SWAYAM, NPTEL, and various private providers. However, research on SRL and learner analytics in the Indian context remains limited. Studies by Baelo et al. [1] and Mangenot [14] have examined online learning in developing countries, but the specific intersection of SRL, learner analytics, and working professionals in regional Indian contexts such as Nashik has not been empirically investigated. This study addresses this gap by providing context-specific evidence on SRL patterns and LA utilisation among working professionals in Nashik District.

3 Research Methodology

This study employs an explanatory sequential mixed-methods design [6]. The target popula-tion comprises working professionals (employed full-time or part-time) aged 21–55 years who are actively enrolled in at least one digital learning course. A stratified random sampling tech-nique was used, with strata defined by industry sector (IT, manufacturing, finance, education, healthcare) and educational level (undergraduate, postgraduate, doctoral). Using Krejcie and Morgan's formula [13], the minimum required sample was 196; 200 valid responses were collected (73.5% response rate from 272 distributed questionnaires).

The quantitative survey instrument comprised three sections: (a) demographic and profes-sional profile, (b) SRL strategy adoption measured using a 20-item Likert scale adapted from the Online Self-Regulated Learning Questionnaire (OSLQ)

[2], and (c) learner analytics awareness and utilisation. A pilot study with 20 respondents demonstrated acceptable reliability (Cron-bach's alpha = 0.89). Qualitative data were collected through 15 semi-structured interviews (35–50 minutes each). Quantitative analysis used SPSS v27.0 (descriptive statistics, Pearson correlations, chi-square tests); qualitative data underwent thematic analysis [4].

4 Results and Discussion

4.1 SRL Strategy Adoption Patterns

Figure 1 presents the distribution of SRL strategy usage frequencies among working profession-als. Self-monitoring emerges as the most frequently adopted strategy, with 65% of respondents reporting they "always" or "often" engage in tracking their learning progress. Goal setting follows closely at 60%, indicating that working professionals generally establish clear learning objectives. However, reflection journaling shows the lowest engagement, with 63% reporting "rarely" or only "sometimes" engaging in reflective practice, suggesting that despite goal setting and monitoring, the critical self-reflection phase of Zimmerman's model is underutilised.

These patterns align with Broadbent and Poon's [3] meta-analytic findings that self-monitoring is more naturally adopted in online environments than reflective strategies. Qualitative interview data reveal that time constraints are the primary barrier to reflection: as one IT professional noted, "After a 10-hour workday and two hours of study, I barely have energy to reflect—I just move to the next module." This temporal dimension of SRL challenge is particularly acute for working professionals and represents a key differentiator from traditional student populations.

Table 1: Demographic and Professional Profile of Respondents (N=200)

Characteristic	**Category**	**Freq.**	**Perc.**
Gender	Male	124	62.0
Female		76	38.0
21–28 years		62	31.0
Age Group	29–36 years	78	39.0
37–44 years		42	21.0
45–55 years		18	9.0
IT/Technology		68	34.0
Industry	Manufacturing	38	19.0
Finance/Banking		35	17.5
Education		32	16.0
Healthcare		27	13.5
Undergraduate		72	36.0
Education	Postgraduate	98	49.0
Doctoral		30	15.0
1–5 years		85	42.5
Experience	6–10 years	68	34.0
Above 10 years		47	23.5

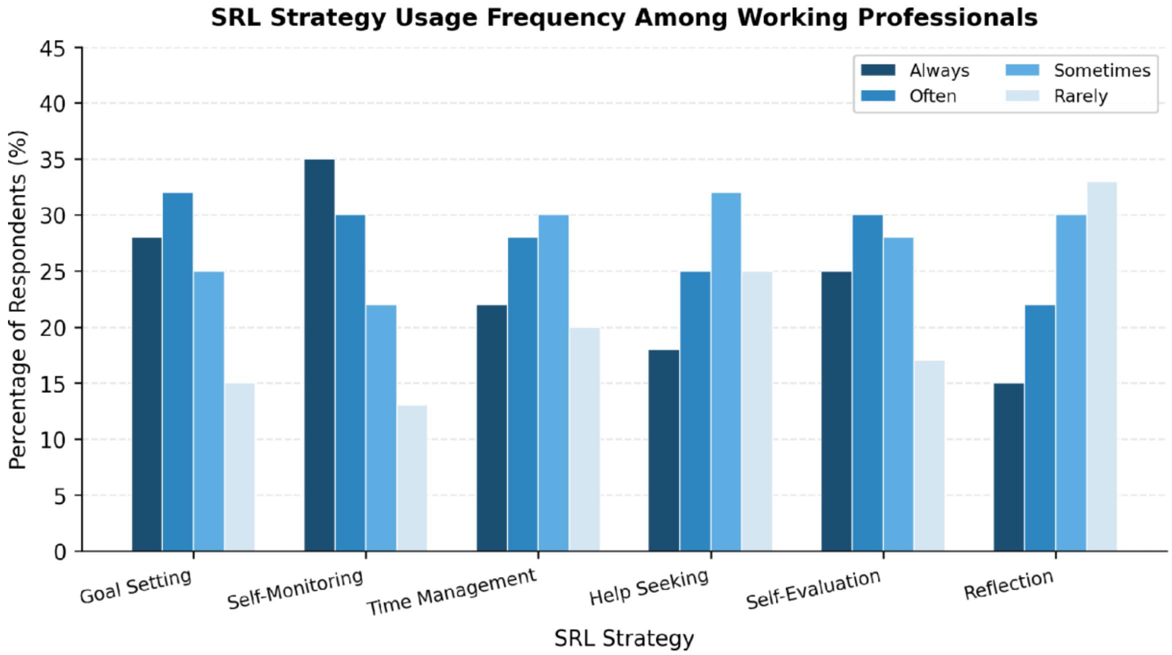

Figure 1: SRL Strategy Usage Frequency Among Working Professionals

Digital Platform Usage

Figure 2 reveals that YouTube Educational content (70%) and Coursera (72%) are the most widely used platforms, followed by Udemy (65%) and University LMS (55%). The popularity of YouTube and Coursera reflects their free or affordable access and diverse course offerings. NPTEL/SWAYAM, despite being government-backed, shows lower adoption (48%), potentially due to awareness gaps or perceived limited industry relevance of course content.

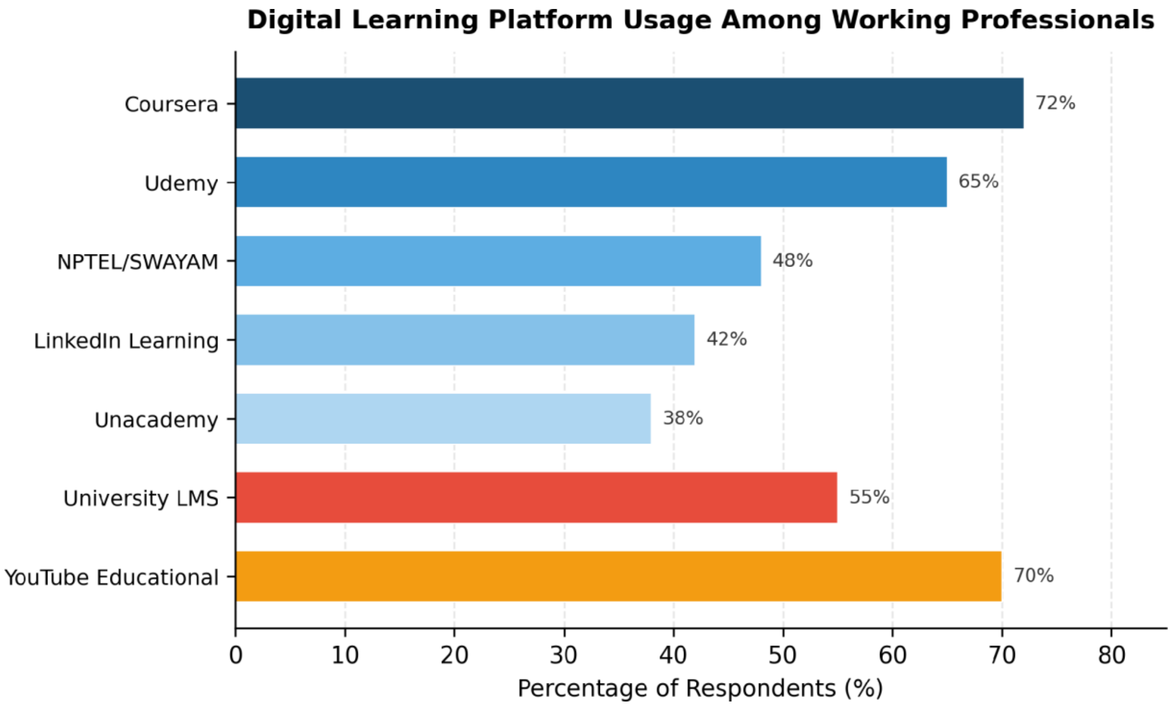

Figure 2: Digital Learning Platform Usage Among Working Professionals

4.2 Learner Analytics Awareness and Utilisation

Figure 3 presents findings on LA awareness and utilisation. While 52% of respondents are aware of LA features on their platforms, only 38% use analytics dashboards regularly, and merely 35% adjust their study strategies based on analytics data. This "awareness-to-action gap" is a central finding: knowledge of analytics availability does not translate into effective utilisation. Encouragingly, 55% find existing LA features helpful, and 68% expressed a desire for more advanced analytics capabilities.

Table 2: Chi-Square Test: LA Awareness and SRL Strategy Adoption

Variable	χ^2	**df**	***p*-value**	**Sig.**
LA Awareness × Goal Setting	14.83	4	0.005	$p < 0.01$
LA Awareness × Self-Monitoring	12.41	4	0.015	$p < 0.05$
LA Utilisation × Self-Evaluation	11.76	4	0.019	$p < 0.05$
LA Utilisation × Reflection	9.58	4	0.048	$p < 0.05$
LA Dashboard Use × Time Mgmt	10.92	4	0.027	$p < 0.05$

Table 2 presents chi-square test results confirming statistically significant associations be-tween LA awareness/utilisation and SRL strategy adoption across all five tested relationships. The strongest association is between LA awareness and goal setting (χ^2 = 14.83, $p < 0.01$), suggesting that awareness of analytics capabilities motivates more effective goal formulation—a forethought-phase activity in Zimmerman's model.

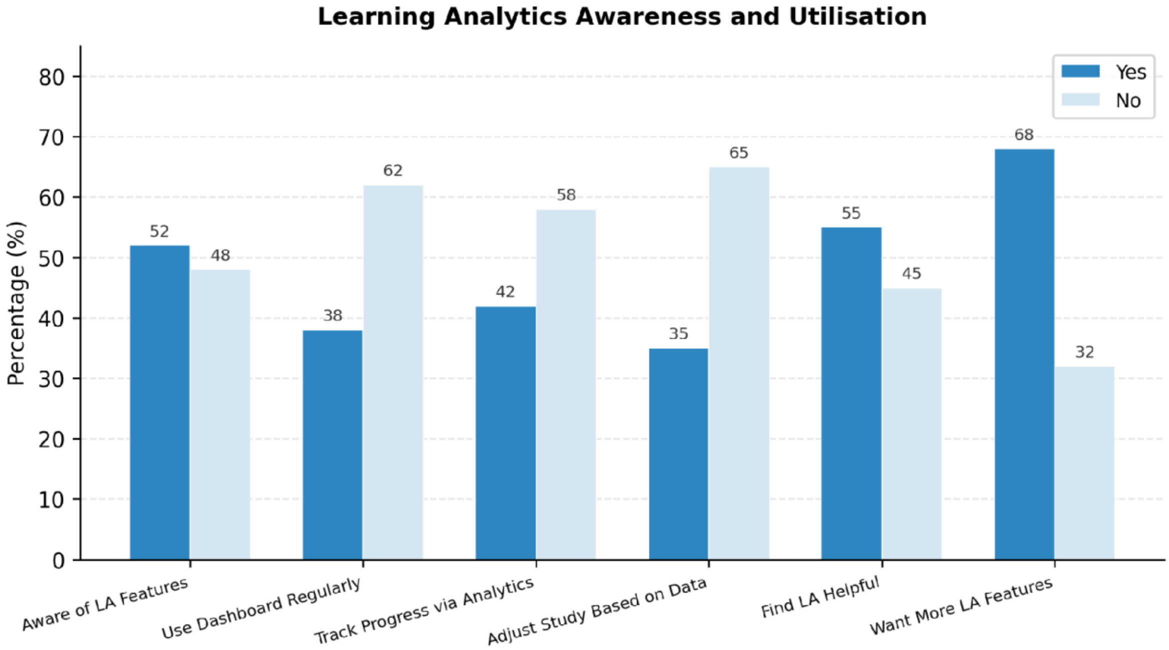

Figure 3: Learning Analytics Awareness and Utilisation

4.3 SRL Engagement and Learning Outcomes

Figure 4 displays the scatter plot of SRL engagement scores versus learning outcome scores, revealing a clear positive trend. Pearson correlation analysis confirms a significant moderate-to-strong positive relationship (r = 0.62, $p < 0.001$), indicating that higher SRL engagement is associated with better learning outcomes. This finding is consistent with meta-analytic evi-dence [3] and extends it to the specific context of working professionals in Nashik.

Qualitative interview data provide explanatory depth to this correlation. High-SRL learn-ers consistently described structured study routines, proactive goal adjustment based on per-formance feedback, and deliberate use of platform analytics to identify knowledge gaps. In contrast, low-SRL learners reported reactive study patterns, difficulty maintaining consistency, and limited engagement with analytics features. As one finance professional explained, “I only check my progress when the platform sends a reminder—I don’t actively seek out the analytics.”

5 Proposed Learner Analytics Integration Framework

Based on the empirical findings, this study proposes a Learner Analytics Integration Framework (Figure 5) that maps specific LA features to the three phases of Zimmerman’s SRL model. The framework addresses the identified awareness-to-action gap by recommending design principles that make analytics not merely informational but actionable within each SRL phase.

The framework illustrates how specific LA features can scaffold each SRL phase: predictive modelling and goal analytics support the forethought phase, real-time dashboards and progress trackers enable the performance phase, and comparative analytics with reflective prompts fa-cilitate the self-reflection phase. The dashed feedback loop from enhanced reflection back to forethought represents the cyclical nature of SRL, where reflective insights inform subsequent goal setting. This framework addresses the study’s key finding that merely providing analytics data is insufficient—LA features must be designed to actively prompt and guide SRL behaviours at each phase.

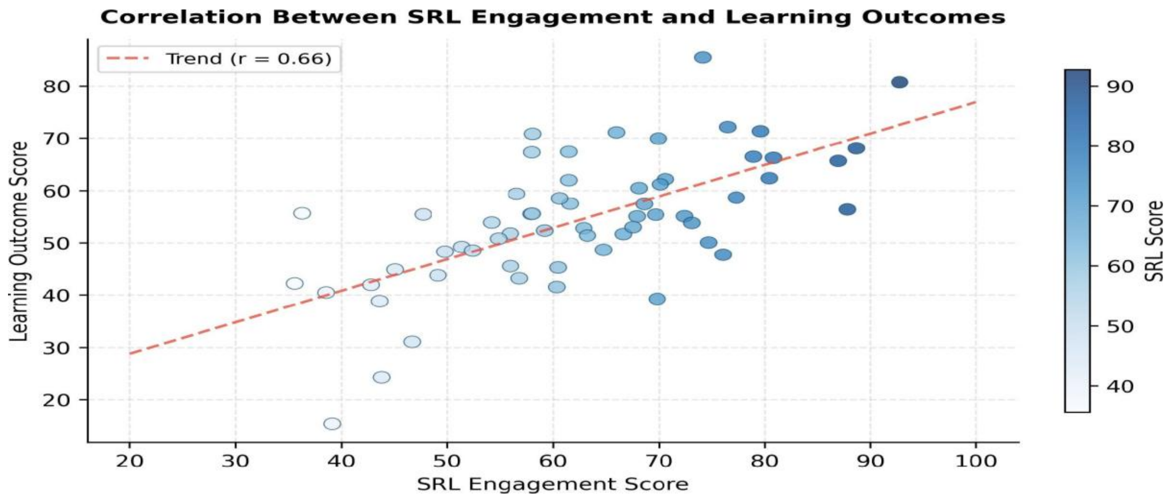

Figure 4: Correlation Between SRL Engagement and Learning Outcomes

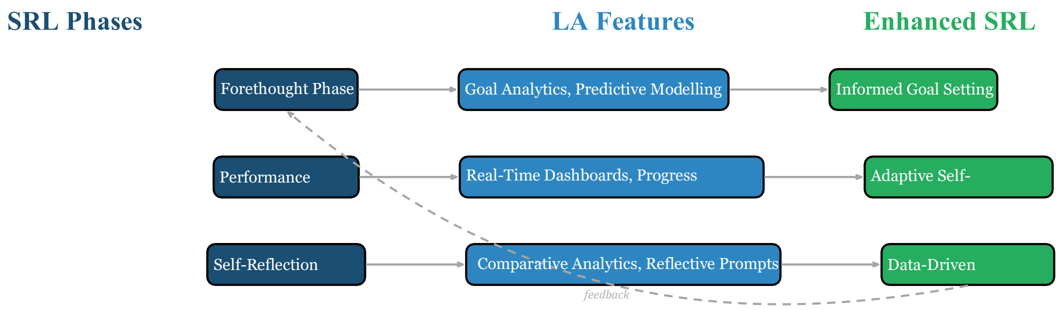

Figure 5: Proposed Learner Analytics Integration Framework

6 Conclusion and Implications

This study provides empirical evidence that working professionals in Nashik demonstrate mod-erate to high SRL engagement, with self-monitoring and goal setting being the most adopted strategies, while reflective practice remains significantly underutilised. The identified “awareness-to-action gap” in learner analytics—where 52% are aware of LA features but only 35% adjust strategies based on analytics data—represents a critical design challenge for digital learning platforms. The significant positive correlation between SRL engagement and learning outcomes ($r = 0.62$) reaffirms the centrality of self-regulation in online learning success.

The proposed LA Integration Framework offers actionable recommendations: platforms should embed analytics within the learning workflow rather than presenting them as separate dashboards, provide contextual prompts that trigger SRL behaviours, and design reflective in-terventions that accommodate the time-constrained schedules of working professionals. For educators, the findings suggest that explicit SRL strategy instruction, combined with guided analytics interpretation, can enhance learning outcomes. For policymakers, the study highlights the need for digital literacy programmes that include analytics interpretation skills as a core competency. Future research should employ longitudinal and experimental designs to establish causal relationships and test the proposed framework across diverse regional contexts in India.

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