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Gamified Learning Analytics to Enhance the Productivity of Software Practitioners in Agile Requirement Change Management

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Abstract**—In the context of technology-enhanced professional learning for software engineering, agile Requirements Change Management (RCM) often suffers from fluctuating motivation and inconsistent collaboration, which reduces practitioners' learning productivity and task performance in authentic project settings. Although prior studies have investigated gamification and productivity in software development, the literature remains limited in explaining how educational technology and learning analytics can be systematically integrated to support continuous competency development for software practitioners. The study seeks to design and evaluate a gamified learning environment to enhance software practitioners' productivity, using measurable indicators, and to identify the most influential core motivational drivers. Involving 32 software practitioners from a development unit, the study employed a log-based ABA quasi-experimental design. During the intervention phase, collaborative participation surged by 99.4%, the task completion rate increased by 16.53 percentage points, work duration with keyboard and mouse rose by 40.2%, and task completion time decreased by 50.8%. These differences were statistically significant, as demonstrated by the Friedman test ($p < 0.001$), with the strongest positive relationships observed for the core drives of unpredictability & curiosity, as well as social influence & relatedness. Theoretically, the findings enrich the literature on technology-supported workplace learning by linking motivational contributions at the Octalysis core-drives level to productivity indicators within the RCM cycle.**

Keywords**—requirement change management, gamification, Octalysis framework, learning analytics, productivity, motivation**

I. INTRODUCTION

Requirement Change Management (RCM) is a key process in software engineering that ensures continuous alignment between dynamic requirements and business objectives while maintaining the quality of the final product [1, 2]. In the context of technology-based education and professional development, RCM activities can be viewed as a form of workplace learning that takes place in a digital work environment: practitioners continuously interpret stakeholder feedback, update software artifacts, and collaborate across roles. Thus, the success of RCM not only impacts project efficiency and organizational competitiveness but also the learning of competencies, knowledge transfer, and the development of digital skills of practitioners on the front lines.

However, RCM implementation is often constrained by human factors, particularly fluctuations in motivation, engagement, and collaboration dynamics, which directly affect schedule accuracy, artifact quality, project costs, and the quality of workplace learning experiences [3–6]. The literature also indicates that the maturity of processes and tools does not automatically mitigate variability in individual behavior and team cohesion, which continue to constrain RCM effectiveness [4, 7]. These impacts are evident in performance indicators such as task completion rates, completion speed, and collaboration intensity, which tend to vary in agile environments characterized by frequent changes [3, 8]. Therefore, from an educational technology perspective, there is a need to design digital interventions that can enhance the motivation and learning productivity of RCM practitioners without adding procedural burdens or increasing process complexity [9].

Recent studies highlight several limitations when viewed from the perspective of improving the learning productivity of software practitioners specifically involved in RCM. Most prior research has focused on generic Information and Communications Technology (ICT) skills, language competencies, or higher education environments, rather than on practitioners' continuous learning in authentic, tool-supported RCM workflows [10, 11]. Proposed models rarely utilize detailed digital traces derived from real project environments, such as issue trackers and work activity logs, to directly measure learning productivity [12, 13].

Conversely, while change management and organizational support are acknowledged as essential components, prior methodologies have not systematically incorporated gamification design, core motivational drivers, and learning analytics into the everyday tools utilized by software practitioners [14, 15]. Consequently, there remains a paucity of empirical evidence connecting specific motivational mechanisms to variations in log-based learning productivity indicators throughout the RCM cycle. This deficiency highlights the need for research that considers RCM as a context for technology-supported workplace learning, employs log-based learning productivity indicators, and empirically assesses gamification interventions grounded in Octalysis framework.

Learning Analytics (LA) has become a powerful tool for monitoring and enhancing workplace learning by utilizing digital activity log data. By integrating learning analytics with performance measurement, organizations can evaluate how interventions contribute to professional development and data-driven decision-making [16, 17]. Despite its potential, the use of log-based learning analytics in real-world software

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engineering environments, particularly in RCM, remains relatively limited. Platforms such as Jira and activity-monitoring tools capture authentic data on how practitioners learn through complex, interdependent, and collaborative tasks within iterative change cycles. This study positions RCM logs and activity traces as valuable learning analytics resources for monitoring and understanding practitioner learning productivity.

Research on integrating learning analytics and gamification into workplace learning is gaining traction alongside digital transformation in software engineering. Learning analytics enables personalized learning paths, identifies skill gaps, and assesses training effectiveness [18]. Gamification boosts motivation through challenges, points, and digital rewards [19]. Together, they create adaptive learning experiences, with gamification data offering insights for analytics to optimize outcomes [20]. Future trends indicate the integration of artificial intelligence and adaptive systems to deliver real-time feedback and personalized learning paths [21], thereby making learning integral to daily work and supporting skill development. In this context, measurable, evidence-based interventions are becoming important, creating opportunities to leverage the digital footprints of work tools for monitoring learning integrated with work.

In response to these identified gaps, this study seeks to address the following specific issues: the absence of an evaluation framework that systematically integrates gamification design based on motivational mechanisms, utilizes digital traces from actual work tools (e.g., issue trackers and activity monitors), and evaluates changes in learning productivity throughout the RCM cycle without imposing additional procedural burdens. This issue is critical because variations in motivation, collaboration, and consistency in implementing change requirements directly influence team throughput, artifact quality, and coordination costs in high-frequency agile environments. The study has two primary objectives. First, it will evaluate the impact of gamification integration on log-based learning productivity indicators within the RCM process. Second, it will identify the predominant core drives underlying variations in these indicators. This information will serve as the foundation for developing incentive policies and sustainable gamification designs. The following research questions have been formulated: Research Question 1: Does the integration of gamification result in measurable changes in learning productivity indicators across the various phases of the ABA model? Research Question 2: Which core drives are most influential in predicting changes in learning productivity indicators during the intervention phase?

To achieve these objectives, this study introduces a behavioral design innovation that integrates into daily workflows to create a gamified learning environment for RCM practitioners. Gamification involves incorporating game-based elements and mechanisms into educational or training settings to boost engagement, persistence, and collaboration [22]. The Octalysis framework serves as a conceptual foundation, aligning game elements with process and learning objectives and team characteristics to define motivational mechanisms. Implementation occurs within the Jira and Hubstaff ecosystems, facilitating a data-driven design–measurement–audit approach from a learning analytics perspective. Theoretically, this study broadens the discourse on technology-supported workplace learning by mapping motivational mechanisms at the core-drive level to log-based learning productivity indicators within the RCM cycle. In practice, it offers a replicable evaluation framework and measurable indicators for designing more sustainable, low-process-burden gamification interventions.

II. LITERATURE REVIEW

A. Technology-Supported Workplace Learning in Software Engineering

Technology-Supported Workplace Learning (TSWL) focuses on seamlessly integrating learning into the daily tasks of software engineering, enabling practitioners to gain knowledge and guidance precisely when needed. Prior research underscores the significance of work-integrated learning systems that facilitate both immediate problem-solving and long-term competency development in dynamic fields where requirements and technologies rapidly evolve [23]. Recent strategies increasingly utilize intelligent and adaptive support, such as personalized recommendations and context-aware decision support, to align learning resources with task demands and individual needs [24–27].

In RCM, the urgency of TSWL is increasingly evident as evolving software requirements demand rapid learning, situational analysis, and knowledge transfer among actors. TSWL systems enable the provision of just-in-time learning resources, expertise recommendations, and collaborative support that help practitioners navigate change effectively [25–28]. In addition, collaborative learning mechanisms, including pair work and LMS support, have been shown to strengthen conceptual understanding and practical application of RCM within teams [22]. However, the implementation of TSWL in real-world settings still faces challenges, including technical complexity, resource constraints, and potential information overload, which hinder learning effectiveness [26, 27]. This condition underscores the need for a technology-based learning model that is not only intelligent and adaptive but also naturally integrated into the RCM workflow to enhance practitioners' learning productivity.

B. Learning Analytics for Monitoring Digital Learning Processes

Learning Analytics (LA) provides a data-driven approach for the collection, measurement, and analysis of learners' digital traces to understand engagement and performance within technology-mediated environments [29, 30]. By facilitating continuous, log-based monitoring and feedback, LA supports timely interventions and self-regulated learning in professional contexts [31–33]. In this study, LA is particularly relevant, as issue trackers and work-activity logs can serve as continuous indicators of how software practitioners learn and perform while managing authentic RCM tasks.

C. Gamification for Professional Learning in Software Engineering

Numerous shows that the integration of points, challenges, badges, or leaderboards consistently increases learning engagement and participation, both in classroom and professional training contexts [34–36]. This increase in engagement directly affects learning outcomes, as evidenced by improvements in academic performance, communication skills, and cross-disciplinary collaboration, including in medical education and language learning [34, 37].

In addition to influencing motivation, gamification has also been shown to strengthen strategic thinking and decision-making through business simulations and team-based activities that allow participants to experience and reflect on critical events [35]. In the context of independent learning, gamification provides structure and feedback that encourages participants to manage their learning pace autonomously, especially in the flipped learning model [37]. However, there are methodological gaps, such as limited long-term metrics; many studies highlighted short-term effects without assessing sustainability and burnout [38]. Research has also often focused on surface indicators and underrecognized mediators, such as team competence or organizational culture [39, 40]. This methodological discrepancy directly impacts the comprehension of the most effective approaches in the field of gamification. Specifically, most of studies treated gamification as a single intervention package and rarely isolated the impact of each motivational driver (core drive) on specific performance outcomes. Consequently, design recommendations were often generalized and complex to transfer across organizations because there was a lack of quantitative evidence identifying which drivers most impact productivity. The absence of standardized instruments for mapping indicators to core drive constructs, along with the lack of core drive-level analytics, results in studies that lack convergence.

Recent evidence in software engineering suggests that incorporating game elements can enhance team engagement and performance in Agile practices through mechanisms such as feedback, rewards, and progress visualization [41, 42]. Positive outcomes have been observed in reflective activities such as sprint retrospectives, in which game-based approaches increase participation and continuous improvement output [43]. In enhancing agile software development processes, gamification is associated with improvements in operational competencies, although motivation reinforcement may be affected by pressure and incentive design [38, 41, 44]. These studies typically situate gamification within the domains of Scrum adoption, retrospectives, and requirements engineering focused on elicitation, without yet addressing the daily work dynamics of the RCM cycle [38, 42, 43]. Much research still relies on self-reports, which are susceptible to bias. In contrast, the use of system-level behavioral data has not become widespread, despite several studies demonstrating the value of process metrics for assessing behavioral change [42, 43, 45]. The literature underscores the necessity of targeted gamification design, as inappropriate implementation can pose risks, including competitive pressure and distortion of work objectives. Based on this evidence, it is crucial to focus research on integrating Octalysis-based design into RCM tools and evaluating their impact through log-based indicators to more robustly test the motivation-behavior-output mechanism.

D. Learning Productivity in Requirement Change Management

Learning productivity is a fundamental component of RCM because the process requires practitioners to quickly understand, analyze, and implement changes to requirements within a dynamic software development ecosystem. The complexity of RCM arises from the need for accurate impact analysis and traceability, given that each change can affect dependencies between requirements and cause system instability [46, 47]. Practitioners' inability to learn these dependency patterns effectively will increase the risk of inaccurate cost and time estimates, particularly in global software development [46]. Therefore, learning productivity is not only related to technical abilities but also to the capacity to adapt to repeated and rapid changes.

The readiness of collaborative technologies and methodological approaches also influences improvements in learning productivity. Collaborative technologies have been shown to accelerate information exchange and cross-location coordination, thereby strengthening teams' collective learning [48]. Similarly, agile practices such as Scrum enable iterative learning through incremental delivery, client involvement, and continuous planning, thereby improving teams' ability to respond to changing needs. [49]. Structured frameworks like the AZ-Model facilitate systematic learning within time and budget constraints in change management [50]. This confirms that learning productivity is a strategic determinant of RCM success; therefore, research must explore mechanisms to accelerate practitioners' learning, particularly through data-driven and digital technologies relevant to daily work.

Within TSWL, learning productivity can be inferred from the extent to which newly acquired knowledge is applied in routine work. Accordingly, this study operationalizes learning productivity in RCM using four log-derived indicators captured by Jira and Hubstaff: task completion rate, collaborative participation in issue handling, active tool-use duration (keyboard and mouse), and task completion time. These indicators collectively reflect output attainment, socio-technical learning through coordination, sustained engagement with work tools, and efficiency gains associated with procedural learning and workflow standardization [51–53]. To connect motivational theory to measurement, Octalysis core drives are treated as mechanism-level constructs, with their perceived salience examined as a predictor of variation in these log-based indicators.

III. MATERIALS AND METHODS

A. Case Study

This research was conducted in the Directorate of Technology and Information System Development at a public university in Indonesia, which routinely manages software requirement changes using Jira (for issue tracking and collaboration) and Hubstaff (for monitoring work-activity intensity). In this setting, the RCM workflow constitutes an authentic technology-supported workplace learning environment in which software practitioners continuously acquire and refine competencies while responding to evolving requirements. The unit was selected because it combines a high intensity of requirement changes across multiple internal projects with mature ICT infrastructures and standardized, auditable process logs, enabling the evaluation of learning productivity without modifying core RCM practices.

Operationally, the RCM cycle in Jira followed a Kanban-based flow that was applied consistently across projects. New change requests were created in the Backlog status, indicating that they had been documented but not yet prioritized. Requests deemed feasible were moved to the "To Do" column once priority and responsible assignee had been defined. Once technical analysis and implementation began, issues were transitioned to "In Progress", during which developers conducted impact analysis, code modifications, and local testing. Completed changes were then moved to "In Review" for peer or designated quality checks, ensuring compliance with standards of quality, security, and consistency, before being marked as "Done" to indicate readiness for release. At any stage, issues could be moved to "Canceled" if they became irrelevant, technically infeasible, or were discontinued for strategic reasons. All status transitions, assignments, comments, worklogs, and mentions were automatically recorded as digital traces, which in this study are treated as learning-analytics data to quantify how practitioners engage with complex RCM tasks over time while maintaining ecological validity of the work setting.

In this study, the learning outcomes of the gamified workplace learning design are characterized by practitioners' demonstrated ability to apply RCM competencies to real-world work tasks. These tasks encompass interpreting stakeholder feedback, conducting impact analyses, coordinating changes, and completing review and closure activities within a Jira-based workflow. As these activities require the application and evaluation of knowledge under dynamic constraints, the targeted outcomes align more closely with higher-order cognitive processes including application, analysis, and evaluation in Bloom's taxonomy rather than mere declarative recall. Consequently, the evaluation focuses on learning productivity, defined as the extent to which practitioners can convert ongoing learning into reliable task throughput, effective collaboration, sustained tool-mediated work engagement, and time-efficient completion. This productivity is captured through detailed digital traces generated by Jira and Hubstaff.

B. Data Collection

Data collection was organized to capture changes in technology-supported workplace learning across three consecutive phases, using a ABA quasi-experimental design (see Fig. 1). For each phase, Jira and Hubstaff logs were harvested and transformed into four indicators representing output, collaboration, activity intensity, and time efficiency, which are interpreted as proxies for learning productivity within the RCM workflow. In addition, a post-study questionnaire captured practitioners' perceptions of the gamified learning design and their motivational experiences. To mitigate the risk of content-level surveillance, the analysis was confined to examining indicator-level traces, such as timestamps, counts, and aggregated activity measures, rather than the contents of messages, code, or keystroke text.

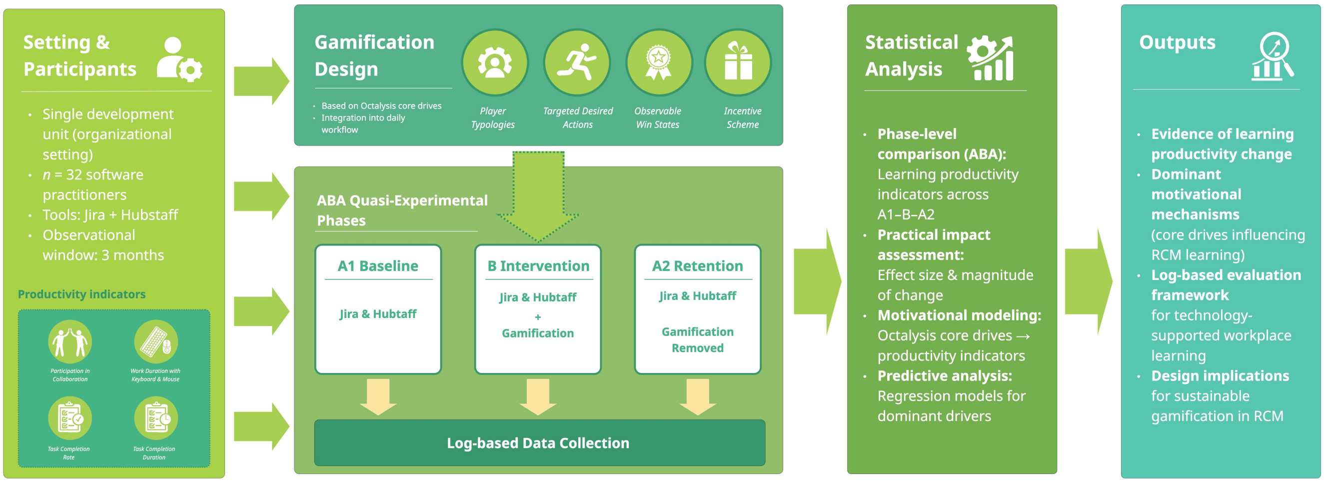


Fig. 1. Study design and analytical workflow.

1) Phase A1 (baseline): Baseline establishment

Phase A1 (first month) was conducted without any gamification stimuli to observe the team's natural learning and working patterns during the RCM cycle. Jira logs were extracted periodically to calculate the number of assigned and completed tasks, collaborative participation on multi-executor issues, comment intensity, and completion duration from opening to closing for each issue. In parallel, Hubstaff recorded the work duration with keyboard and mouse every 10-minute observation slice as an objective proxy for daily engagement with RCM tasks. Extraction procedures and schedules were standardized, forming a consistent learning-analytics pipeline that establishes a baseline profile of workplace learning productivity for each practitioner and for the team.

Before implementing the gamification intervention, we carried out a formative pilot and initial validation with 34 software practitioners from the study unit. This was done to refine both the gamified workplace learning design and the log-based measurement setup. The aim of this baseline step was to gather practical feedback on the clarity, feasibility, and perceived fairness of the gamification rules, specifically regarding missions, points, and recognition mechanisms, as well as the consistency of the data capture workflow. Feedback from this pilot was used to iteratively adjust the intervention configuration before deployment during the ABA phase. The pilot was solely for formative refinement; the inferential analyses presented in this study were conducted on participants with complete log data across all phases.

2) Phase B (intervention): Gamification implementation

In phase B (second month), an Octalysis-based gamification design was activated on top of the existing Jira and Hubstaff configuration, while core RCM workflows and technical practices remained unchanged. In this phase, game elements functioned as instructional supports, providing feedback, recognition, and challenges that scaffolded practitioners' learning as they carried out authentic RCM tasks. Python scripts extracted Jira logs daily to maintain time-series continuity, and Hubstaff data were processed in accordance with the official activity-level guidelines. All configuration changes related to gamification were documented to preserve auditability and to allow replication of the learning design.

3) Phase A2 (retention): Post-withdrawal evaluation

In phase A2 (third month), all gamification elements were deactivated while keeping process and tool configurations constant. Log collection and data processing continued using procedures identical to A1, enabling the examination of whether changes in learning productivity were sustained, attenuated, or reversed once the instructional supports were withdrawn. At the end of A2, a 4-point Likert-scale questionnaire on perceptions of the Octalysis core drives and experiences with the gamified workplace learning environment was administered.

Rationale for the three-month ABA window. We selected a one-month duration per phase to balance validity with feasibility while ensuring sufficient temporal resolution for log-based indicators. Daily tool logs require adequate observations per phase to establish a baseline and detect shifts; a four-week window provides enough working days to reduce weekly seasonality. In agile settings, a month spans at least two iteration cycles, allowing indicators to reflect repeated RCM routines. Using the same duration across phases supports comparability and reduces ambiguity in transitions. This design captures intervention effects and post-withdrawal dynamics under workplace constraints.

C. Participants

This section describes the participants' characteristics, the sampling strategy, and the rationale for the final sample size in the context of an authentic workplace learning setting. Participants in this study were software practitioners who acted as workplace learners within the RCM cycle of the study unit. They held different roles in managing requirement changes including full-stack developers, software analysts, supervisors or team leads, UX designers, and Quality Assurance (QA) personnel, thus representing the end-to-end value chain from analysis and design to implementation, testing, and verification. All practitioners used Jira for issue management and collaboration, while their work-activity intensity was monitored via Hubstaff; consequently, every interaction relevant to the process generates an auditable digital trail of how they interact with RCM tasks and collaborative learning in the workplace.

Participants showed diverse baseline competencies due to their interdependent roles within the Revenue Cycle Management (RCM) cycle, resulting in varied tasks. To mitigate bias from inter-individual differences, the ABA design was analyzed using a within-subject approach, treating each practitioner as their own reference across phases. Where applicable, indicators were contextualized with respect to role responsibilities, and role heterogeneity was considered when discussing the boundary conditions and generalizability of the findings.

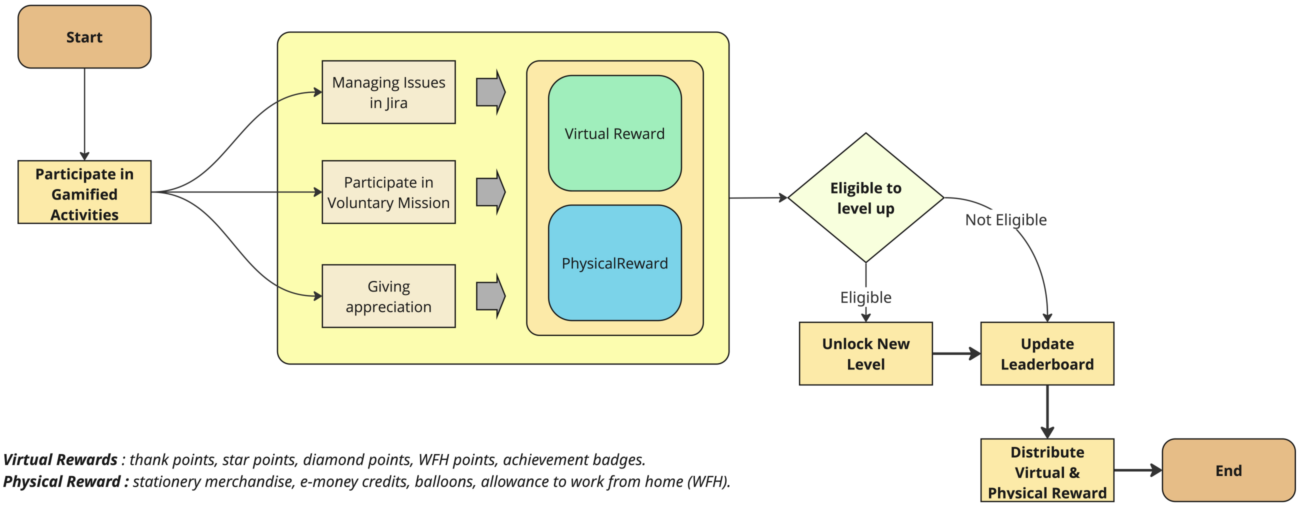
Recruitment followed a purposive strategy to ensure representation of critical roles and a high degree of involvement in daily operations. A total of 34 practitioners were initially invited, based on methodological guidance that within-subject and time-series quasi-experimental designs provide higher statistical power than between-subject designs for similar sample sizes because inter-subject variance can be controlled [54, 55]. The applied statistics literature further suggests that samples of approximately 30–40 are standard and adequate for repeated nonparametric tests and repeated-measures ANOVA when effect sizes are reported [56]. A one-week pilot was conducted before the main study to validate the data-extraction workflow from Jira and Hubstaff and to assess the clarity of procedures from a learner perspective. After log cleaning and completeness checks, two practitioners were excluded due to incomplete questionnaire data, resulting in a final analytical sample of 32 practitioners.

Participant participation was tailored to the quasi-experimental ABA design [54]. In the baseline phase (A1), log data were collected without gamification stimuli to establish a baseline. In the intervention phase (B), gamification elements were activated. Logs were monitored to capture behavioral dynamics and productivity during exposure. In the retention phase (A2), all gamification elements were deactivated, but log collection continued to assess behavioral sustainability or regression. To enrich the quantitative findings, a questionnaire on perceptions of Octalysis core drives, adapted from Chou [57], was distributed to all participants at the end of the study.

In addition to obtaining informed consent and securing institutional approval, we established procedural safeguards for the management of trace data collected from workplace tools. Only the essential metadata necessary for computing study indicators were extracted, and all records were pseudonymized before to analysis. Access to the dataset was restricted to the research team, and findings are reported in an aggregated form to mitigate the risk of re-identification.

D. Gamified Workplace Learning Design for RCM

As part of efforts to improve the effectiveness of software change management, the gamification design in this study was conceived as an instructional strategy for technology-supported workplace learning rather than as a stand-alone entertainment layer. The design was systematically structured so that key behaviors and win states would not only contribute to organizational goals but also scaffold practitioners' acquisition and refinement of RCM competencies. Within the Octalysis framework, target behaviors were selected to provide frequent, meaningful feedback and a sense of tangible progress whenever learners completed specific actions that support the requirement-change process [57]. The resulting gamified workflow, illustrated in Fig. 2, was fully embedded in Jira and Hubstaff so that learning activities coincided with authentic project work.



Virtual Rewards *: thank points, star points, diamond points, WFH points, achievement badges.*
Physical Reward *: stationery merchandise, e-money credits, balloons, allowance to work from home (WFH).*

Fig. 2. Gamification design workflow for requirement change management.

1) *Player typologies*

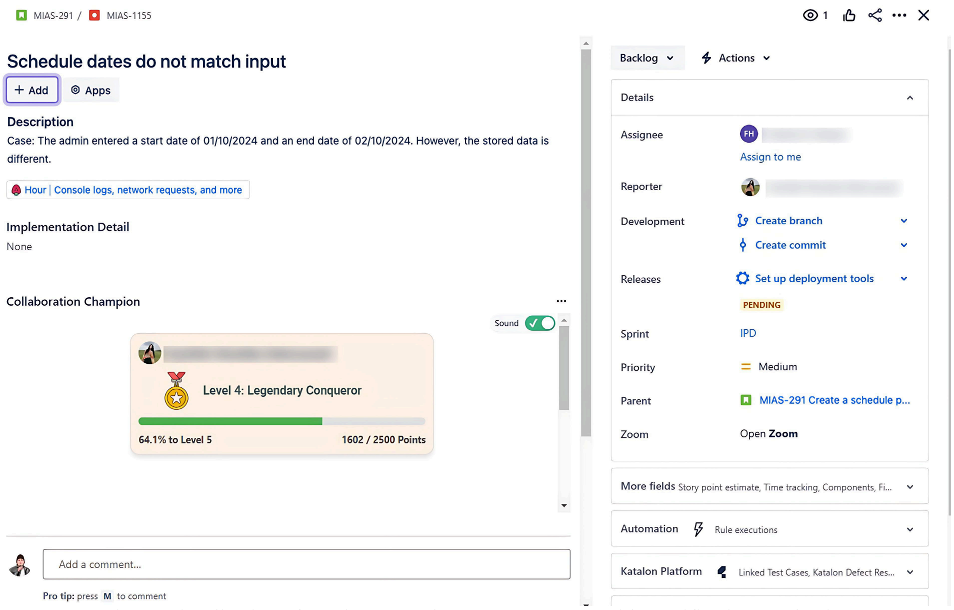
The design established six player typologies drawn from actual job roles so that the gamification mechanics have a high role fit and are contextually relevant: Supervisor (The Sentinel), Software Analyst (Questmaster), Full-stack Developer (Code Knight), Quality Assurance/Tester (Bug Slayer), UX Designer (Pixel Sorcerer), and Admin/Facilitator (Game Master). Role personalization strengthens professional identity, clarifies expectations for contributions, and increases ownership of RCM process outputs. Each typology is linked to a set of behavioral indicators observed in Jira logs so that assessments and feedback are transparent and auditable. The establishment of typologies also enables the differentiation of micro-goals (e.g., bug closure for QA, throughput for developers, requirements clarity for analysts), which are then unified by team goals at the sprint/kanban level.

From an Octalysis perspective, these player typologies primarily mobilize Epic Meaning & Calling (CD1) through role narratives and work impact, Ownership & Possession (CD4) through ownership of tasks and artefacts, and Social Influence & Relatedness (CD5) through role status and social recognition. All three translate role identity into productive motivation by clarifying accountability, accelerating cross-functional coordination, and reducing ambiguity, thereby increasing team throughput.

2) *Targeted desired actions*

To ensure traceability of trace actions, incentives, and outcomes, target behaviors were divided into three clusters. These clusters are based on actual workflows and motivational dynamics. Each cluster is derived directly from process artifacts and activity traces, ensuring that its operational definitions are clear and auditable.

Eight core actions in issue management in Jira comprising Issue Create, Comment Create, Issue Update, Complete Issue, Priority Update, Assign Someone in Issue, Worklog Create, and Mention Someone in Issue are defined as meaningful contribution indicators (see Fig. 3). Counting and throttling rules are applied to minimize the accumulation of points that are proportional to the process value and to prevent the system.



Schedule dates do not match input

Description
Case: The admin entered a start date of 01/10/2024 and an end date of 02/10/2024. However, the stored data is different.

Hour | Console logs, network requests, and more

Implementation Detail
None

Collaboration Champion

[redacted]
Level 4: Legendary Conqueror
64.1% to Level 5
1602 / 2500 Points

Add a comment...
Pro tip: press M to comment

Assignee FH [redacted]
Reporter [redacted]
Releases PENDING
Sprint IPD
Priority Medium
Parent MIAS-291 Create a schedule p...
Zoom Open **Zoom**
More fields Story point estimate, Time tracking, Components, Fi...
Automation Rule executions
Katalon Platform Linked Test Cases, Katalon Defect Res...

Fig. 3. Visualization of requirements change management with gamification mechanisms.

Outside the core workflow, participation in voluntary missions such as contests, quizzes, polling, and challenges was orchestrated to encourage exploration, knowledge sharing, and peer learning. Each mission had explicit assessment criteria regarding quality, speed, and contribution, ensuring that the results could be traced and replicated.

Appreciation between colleagues was managed through Thanks Mate/Perk and can be combined with social gifting. This mechanism enabled rapid reinforcement of helpful behavior, high-quality code reviews, and cross-role support; transparent governance maintains fairness and avoids personal bias.

Motivationally, the overall design of desired actions maps core actions to Development & Accomplishment (CD2) through progress and achievement, links them to team goals to activate Epic Meaning & Calling (CD1), provides a sense of ownership through Ownership & Possession (CD4), and fosters social influence, Social Influence & Relatedness (CD5), through visibility of contributions and appreciation. The setting of rhythm and deadlines (CD6), mission variation and surprises (CD7), and the risk of missing opportunities (CD8) serve as temporal reinforcers. This combination triggers an increase in completion rates, collaboration, activity intensity, and time efficiency through rapid feedback and auditable rules.

3) Observable win states

To reduce uncertainty and make the value of contributions explicit, the system uses four easily audited win states: Level (individual progress based on accumulation and consistency), General Winner (highest combined score across Diamond/Star/Thank/WFH), Group Role Winner (best winner in each role), and Team Winner (highest team accumulation). At the action level, win states are mapped as follows: Core issue management activities accumulate Diamond Points; participation in voluntary activities (contests/quizzes/polls/challenges) earns Star Points; peer appreciation (Thanks Mate/Perk) earns Thank Points; and certain accumulations can be converted into remote working allowance (WFH Points). The establishment of this win-state creates a traceable path from behavior to recognition to reward, while facilitating quantitative evaluation of the design's impact on learning productivity indicators.

From a core drives perspective, the win-state activates Development & Accomplishment (CD2) through badges, levels, and leaderboards; reinforces Social Influence & Relatedness (CD5); Empowerment of creativity & feedback (CD3) through General's Carrot for appreciation/point transfer and quick feedback via dashboard; and supports Epic Meaning & Calling (CD1) through markers of collective achievement. The clarity of the win-state reduces ambiguity of purpose, accelerates decision-making, and encourages consistent of behavior until closure.

4) Incentive scheme

The incentive scheme has been meticulously designed in layers to stimulate both intrinsic and extrinsic motivation without creating an administrative burden. Virtual incentives encompass Diamond Points (contributions to issues), Star Points (participation in voluntary activities), Thank Points (social appreciation between colleagues), WFH Points (redeemable work-from-home rights), and Badges (special achievements). Merchandise, e-money, scheduled work-from-home rights, and symbolic tokens (e.g., balloons to boost team morale) are physical incentives. Reward governance is characterized by a daily and weekly rhythm to sustain continuous participation and mitigate fatigue. All configurations, throttling rules, action-to-win-state mapping, and point parameters are documented to facilitate replication and auditing while enabling data-driven calibration based on changing needs and sprint rhythms.

During the gamification intervention phase, virtual rewards were conferred immediately upon the completion of validated activities within the gamified workflow, thereby facilitating continuous feedback loops. Physical rewards were distributed based on accumulated rankings, which combined (i) daily individual point standings and (ii) weekly aggregated points at the role-group and team levels. Additionally, WFH points were treated as expirable credits to encourage timely utilization and prevent long-term accumulation; unused WFH points expired after a specified validity period. To mitigate the risk of "gaming the system", we implemented rule constraints and continuous monitoring, including the validation of eligible events, filtering of duplicate/invalid events, and periodic review of anomalous point patterns. Based on reported feedback and observed edge cases, we release routine configuration patches to refine rule interpretations and close exploitation loopholes during the intervention phase.

E. Data Analysis

Data analysis followed a learning analytics perspective, using statistical procedures to examine how the gamified workplace learning design affected changes in learning productivity across phases. Numerical data for each indicator were analyzed in stages. The initial stage assessed normality using the Shapiro-Wilk test, which is well-suited to small and medium-sized samples, to determine whether parametric or non-parametric techniques were appropriate. When the normality assumption was satisfied ($p > 0.05$), repeated-measures ANOVA was applied to assess mean differences across ABA phases. When the assumption was violated ($p < 0.05$), the Friedman test and Wilcoxon signed-rank test were used to detect significant changes between phases with greater robustness to non-normal distributions.

In addition to assessing statistical significance, we evaluate the practical relevance of changes by examining phase-level descriptive shifts, such as means and relative differences, and employing effect-size statistics where relevant. This includes using partial ηp^2 for repeated-measures ANOVA and concordance-based indices for non-parametric tests.

The analysis of the questionnaire data commenced with descriptive statistics, which were used to provide an overview of the trends and distributions of practitioners' responses across variables. Subsequently, validity and reliability tests were conducted to examine internal consistency among items within the construct and to assess construct validity, thereby evaluating the extent to which the indicators accurately represent the variables being measured.

Furthermore, Spearman's rank correlation is used to assess the association between core gamification drivers and productivity indicators. This analysis is deemed appropriate for ordinal and non-parametric data. To examine the influence of core drives on productivity in greater depth, employed multiple linear regression to determine the contribution and dominance of each core drive in explaining changes in practitioners' productivity during the intervention period. Using a structured, layered statistical approach, this study is expected to provide a robust empirical assessment of the efficacy of integrating gamification in enhancing work productivity in the domain of RCM.

IV. RESULT

A. Effects of Gamified Workplace Learning on Learning Productivity

The experimental validation examined how an Octalysis-based gamified workplace learning environment, embedded in the team's daily work tools (Jira and Hubstaff), influenced the learning productivity of software practitioners engaged in RCM. The analysis addressed two main questions: first, whether the gamification intervention produced measurable improvements in learning productivity indicators during the intervention phase B compared with the baseline phase A1; and second, whether these improvements were sustained, attenuated, or disappeared after the intervention was withdrawn in the retention phase A2. The ABA design was selected to attribute observed changes as clearly as possible to the instructional intervention while maintaining ecological validity in a real work setting.

Descriptive statistics were employed to examine patterns across phases concerning four indicators of learning productivity, as illustrated in Fig. 4. The green dots denote the mean values, while the vertical bars indicate the Standard Deviation (SD). Collaborative participation increased from 70.19 instances in phase A1 to 140.00 instances in phase B, subsequently declining to 45.66 instances in phase A2. The task completion rate rose from 41.30% in phase A1 to 57.83% in phase B, before decreasing to 15.10% in phase A2. The work duration with input devices increased from 58.38 h in phase A1 to 81.83 h in phase B, followed by a reduction to 16.01 h in phase A2. The duration of task completion exhibited a downward trend, decreasing from 786.97 h in phase A1 to 386.78 h in phase B, and further declining to 291.54 h in phase A2. These patterns suggest that gamification enhanced collaboration and output during phase B, while the improved time efficiency observed until the final phase indicates post-withdrawal retention.

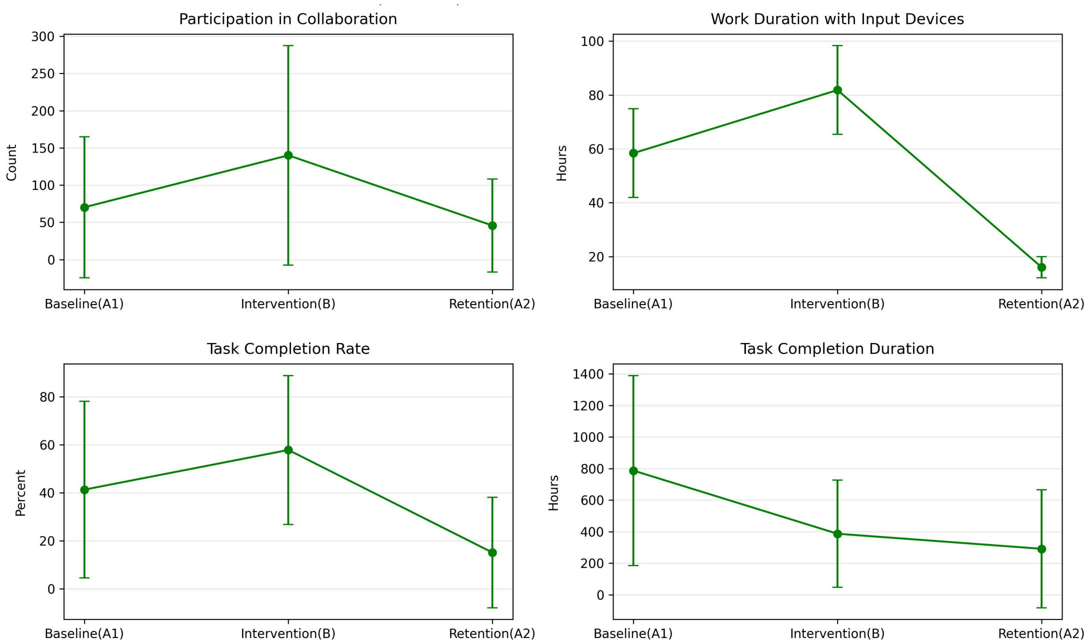


Fig. 4. Descriptive comparison of the four learning-productivity indicators across ABA phases.

Inferential analysis commenced by evaluating distributional assumptions to identify the suitable statistical test. For transparency, Shapiro–Wilk statistics are presented for each indicator: collaborative participation ($p < 0.05$), task completion rate ($p < 0.05$), and task completion duration ($p < 0.05$) all deviated from normality across phases, whereas keyboard and mouse activity duration did not (all phases $p > 0.05$). Consequently, Friedman/Wilcoxon procedures were applied to the non-normal indicators, while repeated-measures ANOVA was used for keyboard and mouse activity duration.

The Friedman test results for collaborative participation revealed significant variation across the three phases, reflected by a chi-square value of 32.71 and a p-value of less than 0.001. Subsequent Wilcoxon paired tests showed a substantial increase from phase A1 to B ($Z = -4.12$, $p < 0.001$), a significant decrease from B to A2 ($Z = -4.94, p < 0.001$), and a lower level in A2 compared to A1 ($Z = -2.17, p = 0.030$) (see Table 1). The overall phase effect was substantial, as indicated by Kendall's W = 0.51, suggesting that the observed changes were not only statistically significant but also of practical importance. The pairwise Wilcoxon effects were notably significant for A1–B ($r = 0.73$) and B–A2 ($r = 0.87$), with a moderate residual difference observed between A1 and A2 ($r = 0.38$).

For the task completion rate, the Friedman test also indicated significance ($\chi^2 = 30.33, p < 0.001$), although the increase from A1 to B was not conventionally significant ($Z = -1.72, p = 0.085$). The decrease from B to A2 was significant ($Z = -4.13, p < 0.001$), and A2 was significantly lower than A1 ($Z = -3.47, p < 0.001$). The overall phase effect was moderate to large, as indicated by Kendall's $W = 0.47$. While the increase from A1 to B did not achieve conventional statistical significance ($r = 0.30$), the decreases observed from B to A2 ($r = 0.73$) and from A1 to A2 ($r = 0.61$) were substantial. These findings suggest that the gains in output were notably sensitive to the withdrawal of reinforcement. These results indicate that the efficiency of task completion is strongly influenced by the application of gamification reinforcement, which does not persist once the reinforcement is removed.

Table 1. Summary of Friedman and Wilcoxon test results for variable indicators

Indicator	Friedman Chi-Square (df = 2)	*p*-value Friedman	Wilcoxon Baseline vs Intervention (*Z*, *p*)	Wilcoxon Intervention vs Retention (*Z*, *p*)	Wilcoxon Baseline vs Retention (*Z*, *p*)
Participation in collaboration	32.71	<0.001	$Z = -4.12, p < 0.001$	$Z = -4.94, p < 0.001$	$Z = -2.17, p = 0.030$
Task completion rate	30.33	<0.001	$Z = -1.72, p = 0.085$	$Z = -4.13, p < 0.001$	$Z = -3.47, p < 0.001$
Task completion duration	17.22	<0.001	$Z = -3.48, p < 0.001$	$Z = -1.52, p = 0.130$	$Z = -3.94, p < 0.001$

Regarding task completion duration, the Friedman test yielded a significant result ($\chi^2 = 17.22, p < 0.001$), showing shorter durations in phase B compared to A1 ($Z = -3.48, p < 0.001$). The difference between B and A2 was not significant ($Z = -1.52, p = 0.130$), whereas A2 was consistently shorter than A1 ($Z = -3.94$, $p < 0.001$). The overall phase effect was characterized as small to moderate, with Kendall's $W = 0.27$. Pairwise comparisons revealed a substantial reduction from phase A1 to phase B ($r = 0.62$) and from phase A1 to phase A2 ($r = 0.70$). In contrast, the difference between phases B and A2 was minor ($r = 0.27$), indicating a partial retention of time-efficiency gains. Temporal efficiency shows better retention post-withdrawal, likely due to process learning, workflow standardization, or partial automation.

Table 2. Summary of repeated measures ANOVA on work duration with keyboard and mouse.

Analysis	Value
Mean Baseline	58.38 h
Mean Intervention	81.83 h
Mean Retention	16.01 h
Partial Eta Squared	0.926
Partial Eta Squared (Within)	Linear: 0.902; Quadratic: 0.942
Mauchly's Test of Sphericity	$W = 0.989$; $\chi^2(2) = 0.318$; $p = 0.853$
Pairwise Comparison Baseline vs Intervention	Δ=+23.46 h; $p < 0.001$
Baseline vs Retention	Δ=−42.37 h; $p < 0.001$
Intervention vs Retention	Δ=−65.83 h; $p < 0.001$

Repeated measures ANOVA confirmed sphericity assumption fulfillment, with Mauchly's $W = 0.989, \chi^2(2) = 0.318$, and $p = 0.853$, indicating no violation during work duration with keyboard and mouse. Analysis revealed a substantial phase effect size ($\eta^2 p = 0.926$; see Table 2), suggesting that phase membership explained a very large proportion of variance in keyboard and mouse activity duration, and supporting a practically meaningful intervention effect in the workplace setting. These findings support the conclusion that gamification reinforcers enhance work intensity, though this effect is transient and diminishes once the reinforcers are removed.

B. Relationships Between Learning Productivity Indicators and Octalysis Core Drives

The second set of analyses examined how learners' perceptions of motivational factors within the Octalysis framework were associated with the four learning productivity indicators during the intervention phase. Spearman's correlation analysis (see Fig. 5) was used because the perception data were ordinal and did not follow a normal distribution. The results showed a strong positive association between collaborative participation and Social Influence & Relatedness (CD5), along with a moderate association with Epic Meaning & Calling (CD1). These patterns indicate that collaboration-intensive learning behavior in RCM is closely tied to social encouragement and a sense of shared mission.

	CD1 Epic Meaning	CD2 Accomplishment	CD3 Empowerment	CD4 Ownership	CD5 Social Influence	CD6 Scarcity	CD7 Unpredictability	CD8 Avoidance	Collaborative Participation	Input Device Usage Time	Completion Time	Completion Rate
CD1 Epic Meaning	1.00	0.29	0.26	-0.12	0.07	0.08	-0.28	0.36	0.22	0.25	0.03	0.16
CD2 Accomplishment	0.29	1.00	0.27	0.08	0.29	0.15	0.01	0.50	0.53	0.15	0.33	0.42
CD3 Empowerment	0.26	0.27	1.00	0.18	0.22	-0.02	0.01	0.22	0.22	0.20	0.11	0.32
CD4 Ownership	-0.12	0.08	0.18	1.00	0.18	0.47	-0.06	0.38	0.33	0.21	0.29	0.35
CD5 Social Influence	0.07	0.29	0.22	0.18	1.00	0.24	0.53	0.53	0.76	0.67	0.83	0.80
CD6 Scarcity	0.08	0.15	-0.02	0.47	0.24	1.00	0.33	0.44	0.46	0.38	0.59	0.52
CD7 Unpredictability	-0.28	0.01	0.01	-0.06	0.53	0.33	1.00	0.15	0.44	0.42	0.74	0.66
CD8 Avoidance	0.36	0.50	0.22	0.38	0.53	0.44	0.15	1.00	0.71	0.33	0.63	0.61
Collaborative Participation	0.22	0.53	0.22	0.33	0.76	0.46	0.44	0.71	1.00	0.57	0.83	0.83
Input Device Usage Time	0.25	0.15	0.20	0.21	0.67	0.38	0.42	0.33	0.57	1.00	0.60	0.71
Completion Time	0.03	0.33	0.11	0.29	0.83	0.59	0.74	0.63	0.83	0.60	1.00	0.88
Completion Rate	0.16	0.42	0.32	0.35	0.80	0.52	0.66	0.61	0.83	0.71	0.88	1.00

Fig. 5. Summary of Spearman's correlation test between Octalysis core drive and learning productivity indicators.

Keyboard and mouse use duration correlated strongly with CD5 and moderately with CD1 and Unpredictability & Curiosity (CD7), suggesting that social recognition and curiosity-driven elements are linked to sustained digital tool engagement. Task completion output showed strong correlations with CD7 and CD5, indicating uncertainty, surprise, and social influence drive productive learning activity. Task completion duration exhibited a complex correlation profile, typical for temporal efficiency indicators shaped by motivational dynamics and process learning. To disentangle the contributions of each core drive, multiple linear regression models were estimated for each indicator.

C. Contribution of Core Drives to Participation in Collaboration

Multiple regression analyses were conducted to estimate the unique influence of each Octalysis core drive on the learning productivity indicators, controlling for the other drives. For the collaborative participation indicator, the model (see Table 3) showed a good fit ($R = 0.87$, $R^2 = 0.76$, adjusted $R^2 = 0.68, p < 0.001$), with CD1 emerging as a significant predictor ($\beta \approx 0.457$, $p = 0.003$). This suggests that, when other motivational factors are held constant, the perceived meaning and calling associated with work account for a substantial proportion of the variance in how frequently practitioners contribute to multi-actor issues and cross-role coordination.

Table 3. Regression results for collaborative participation

Predictor	**Beta (Unstd.)**	**Beta (Std.)**	***p***	***R***	***R*²**	**Adj. *R*²**
CD1	35.480	0.457	0.003	0.87	0.76	0.68
CD2	9.557	0.236	0.063			
CD3	−8.896	−0.188	0.145			
CD4	4.292	0.075	0.613			
CD5	10.877	0.262	0.107			
CD6	7.232	0.119	0.397			
CD7	10.621	0.323	0.061			
CD8	12.320	0.188	0.252			
				Sig. model		< 0.001

D. Contribution of Core Drives to Task Completion Rates

The regression model for task completion rate, the regression model (see Table 4) exhibited a very high level of fit ($R = 0.96$, $R^2 = 0.93$, adjusted $R^2 = 0.90$, $p < 0.001$), indicating that variations in motivational constructs accounted for a large share of the variance in output. Unpredictability & Curiosity (CD7) was the strongest predictor ($\beta \approx 0.523, p < 0.001$), followed by Social Influence & Relatedness ($CD5$; $\beta \approx 0.343, p = 0.001$) and Epic Meaning & Calling ($CD1$; $\beta \approx 0.224$, $p = 0.008$). This pattern aligns with the correlation findings and indicates that exploratory elements, combined with social reinforcement and meaningful narratives, are particularly effective in accelerating task completion in a complex RCM learning environment.

Table 4. Regression results for task completion rate

Predictor	**Beta (Unstd.)**	**Beta (Std.)**	***p***	***R***	***R*²**	**Adj. *R*²**
CD1	3.663	0.224	0.008	0.96	0.93	0.90
CD2	1.710	0.201	0.007			
CD3	0.451	0.045	0.525			
CD4	2.138	0.178	0.042			
CD5	2.990	0.343	0.001			
CD6	1.682	0.131	0.105			
CD7	3.617	0.523	0.000			
CD8	−0.107	−0.008	0.932			
				Sig. model		< 0.001

E. Contribution of Core Drives to Work Duration Using Keyboard and Mouse

Regarding the work duration with keyboard and mouse use, the model in Table 5 showed an adequate fit ($R = 0.80, R^2 = 0.64$, adjusted $R^2 = 0.51, p = 0.001$). Two positive and significant predictors were identified: CD1 ($\beta \approx 0.418, p = 0.009$) and CD5 ($\beta \approx 0.474$, $p = 0.023$). These findings imply that when learners perceive their work as meaningful and experience transparent social recognition, they are more likely to invest time and effort interacting with digital tools, as reflected in higher activity levels.

Table 5. Regression results for work duration with keyboard and mouse

Predictor	**Beta (Unstd.)**	**Beta (Std.)**	***p***	***R***	***R*²**	**Adj. *R*²**
CD1	4.180	0.481	0.009	0.80	0.64	0.51
CD2	0.435	0.096	0.529			
CD3	−0.493	−0.093	0.553			
CD4	0.606	0.095	0.608			
CD5	2.196	0.474	0.023			
CD6	1.487	0.218	0.215			
CD7	1.225	0.333	0.115			
CD8	−1.730	−0.236	0.248			
				Sig. model		0.001

F. Contribution of Core Drives to Task Completion Duration

The model reported in Table 6 demonstrated a high degree of fit for task completion duration ($R = 0.91, R^2 = 0.83$, adjusted $R^2 = 0.77, p < 0.001$). The analysis identified three core drives that emerged as significant predictors. CD7 ($\beta \approx 0.451, p = 0.004$), CD5 ($\beta \approx 0.331, p = 0.020$), and Loss & Avoidance ($CD8$; $\beta \approx 0.286, p = 0.047$). The findings indicate that elements designed to stimulate curiosity, social influence, and mechanisms that subtly encourage loss & avoidance can function as behavioral nudges, prompting learners to complete tasks more efficiently.

Across all models, the combined evidence indicates that a subset of core drives consisting of Unpredictability & Curiosity (CD7), Social Influence & Relatedness (CD5), and Epic Meaning & Calling (CD1) consistently explain meaningful variance in indicators of learning productivity. In the context of technology-supported workplace learning for RCM, these drives appear to be key levers through which gamified instructional design can shape collaboration, throughput, engagement with tools, and time efficiency.

Table 6. Regression results for task completion duration

Predictor	**Beta (Unstd.)**	**Beta (Std.)**	***p***	***R***	***R*²**	**Adj. *R*²**
CD1	37.530	0.210	0.082	0.91	0.83	0.77
CD2	3.345	0.036	0.730			
CD3	−15.580	−0.143	0.190			
CD4	−7.914	−0.060	0.634			
CD5	31.633	0.331	0.020			
CD6	27.993	0.200	0.102			
CD7	34.140	0.451	0.004			
CD8	43.058	0.286	0.047			
				Sig. model		< 0.001

V. DISCUSSION

The present study investigated the effects of an Octalysis-based gamified learning layer, integrated into Jira and Hubstaff, on the learning productivity of software practitioners within an agile RCM workflow Across the phases, the intervention (B) produced significant changes in collaboration, activity intensity, and time efficiency: collaborative participation nearly doubled from $M = 70.19$ (A1) to $M = 140.00$ (B; $+99.5\%$), then decreased $M = 45.66$ (A2). Meanwhile, keyboard and mouse duration increased from 58.38 hours (A1) to 81.83 hours (B; $+40.2\%$) and then dropped to 16.01 hours (A2). Time efficiency showed the most substantial improvement, with completion duration decreasing from 786.97 h (A1) to 386.78 h (B; -50.9%) and remaining lower in A2 (291.54 h). These changes suggest enhanced coordination intensity and faster convergence from change handling to closure during the intervention, which is operationally significant for agile RCM, where coordination overhead and iteration cycles influence delivery reliability. However, the post-withdrawal reduction in most indicators suggests that several gains depended on continued reinforcement. In contrast, the more persistent time-efficiency pattern may reflect partial proceduralization, such as streamlined coordination routines or workflow standardization.

A critical analysis necessitates the consideration of boundary conditions and alternative explanations. Firstly, a portion of the intervention's uplift may be attributed to a reactivity effect, wherein the heightened salience of goals, feedback, and visibility temporarily amplifies effort, independent of substantive competence development. Secondly, indicators derived from logs are sensitive to task composition, change complexity, and workload distribution; consequently, output-oriented measures may exhibit less consistent responses compared to collaboration- and activity-related traces. This aligns with the paired A1–B comparison for completion rate not achieving conventional significance ($p = 0.085$), suggesting that throughput gains may be contingent upon assignment patterns and the heterogeneity of change requests. Thirdly, the attenuation observed following withdrawal indicates that specific behavioral changes were contingent on reinforcement rather than being fully internalized. Nonetheless, the persistence of time-efficiency improvements implies that certain benefits may endure beyond incentives when mediated by process adaptations, such as expedited decision convergence or enhanced coordination practices, rather than by transient effort intensification.

The core-drive contribution pattern reveals that Unpredictability & Curiosity (CD7) and Social Influence & Relatedness (CD5) were predominant across most indicators, with additional contributions from Epic Meaning & Calling (CD1) and context-specific effects of Loss & Avoidance (CD8). This observation is consistent with previous findings that gamification can enhance motivation, persistence, and performance when game elements are closely integrated with authentic tasks and short feedback cycles [58, 59]. Furthermore, it extends this evidence by identifying which motivational levers most effectively align with trace-based productivity indicators in an RCM workflow. The prominence of CD5 corroborates earlier research highlighting reputation, peer recognition, and relatedness as key drivers of sustained participation and collaborative learning [60]. Concurrently, the significant role of CD7 aligns with the notion that novelty, challenge, and uncertainty can rapidly engage individuals in learning-relevant tasks [61, 62]. Notably, the observed post-withdrawal attenuation is consistent with reports of short-term reinforcement effects that diminish when stimuli are removed [63, 64], suggesting that CD7/CD5-driven enhancements may be potent but time-sensitive, unless the design evolves toward autonomy- and competence-supporting mechanisms. From a broader perspective of motivational theory, the predominance of CD5 can be interpreted as indicative of relatedness needs, while CD7 corresponds to curiosity-driven competence development. Together, these elements suggest that workplace learning outcomes are enhanced when both social belonging and exploratory challenges are concurrently supported.

From a practical perspective, the findings suggest that gamification in agile RCM should be deployed as a governed, adjustable layer rather than a one-off reward campaign. Organizations can prioritize (i) calibrated variation to sustain CD7 (e.g., periodically refreshed challenges and time-bounded missions), (ii) transparent, contribution-based social recognition to operationalize CD5 without distorting teamwork, and (iii) meaning cues embedded in routine artifacts (CD1), such as issue narratives tied to user impact, sprint goals, and shared milestones. Given the sharp decline after withdrawal, a tapering strategy is recommended: progressively shift reinforcement from tangible rewards toward peer recognition and mastery-oriented feedback, and maintain a feedback rhythm that avoids fatigue. Practically, this can be implemented with minimal overhead by automating feedback and using dashboards derived from Jira/Hubstaff logs to monitor whether collaboration and activity intensity remain stable as reinforcement is reduced.

Beyond methodological considerations, the implementation of gamified learning analytics within workplace environments necessitates careful attention to ethical implications. Feedback driven by metrics may be perceived as increased surveillance, potentially influencing behavior, stress levels, and team dynamics. Furthermore, these indicators may interact with role-specific responsibilities and uneven task distribution, posing risks to fairness if interpreted as directly comparable across different roles. Therefore, a responsible implementation should prioritize transparent communication, proportionate feedback, and governance mechanisms that prevent metrics from becoming punitive appraisals or exacerbating inequities in recognition and workload. Additionally, organizations should consider digital-inequality risks, such as differential access to stable connectivity, proficiency with tools, or role-based opportunities to earn points or recognition, which may unintentionally reinforce existing inequities if analytics and rewards are applied uniformly without fairness-aware calibration.

Theoretically, this study contributes to the field of technology-supported workplace learning by empirically mapping core-drive mechanisms to log-based learning productivity indicators within an authentic RCM context. The findings support a distinction between (a) social–behavioral indicators (such as collaboration and activity intensity), which are more sensitive to reinforcement, and (b) structural efficiency indicators (such as completion time), which may exhibit greater durability when mediated by process routines. Additionally, the integration of Jira process logs and Hubstaff activity traces demonstrates a replicable approach to the auditable evaluation of workplace learning interventions, addressing calls for data-driven measurement that remains embedded in real work systems rather than isolated training platforms.

Several limitations merit consideration. The study was conducted in a single unit over three months without an external control group; consequently, workload fluctuations, project cycles, or novelty effects cannot be excluded. While keyboard and mouse activity serves as an objective proxy for intensity, it does not measure learning quality, task complexity, or affective states. Building on the observed transience after withdrawal and durability of time efficiency, future research should (i) explore maintenance designs that gradually reduce reinforcement, (ii) replicate the framework in multi-site settings across varying RCM maturity levels, and (iii) incorporate quality-oriented outcomes linked to RCM competence (e.g., rework rate, defect-related revisions, change-impact analysis quality, and review effectiveness). Longitudinal studies are needed to test whether time-efficiency gains persist beyond short cycles and distinguish durable procedural learning from temporary acceleration effects. Given the sensitivity of output measures to task mix, studies should stratify analyses by role and change complexity, and develop fairness-aware indicators that account for workload allocation. Team culture may moderate perceptions of gamification and analytics, thereby affecting engagement and post-withdrawal persistence. Finally, adaptive gamification can be assessed by adjusting challenge, levels, recognition patterns, and mission types based on individual- and team-level analytics, while monitoring perceived surveillance and trust to ensure ethical sustainability.

VI. CONCLUSION

This study examined how an Octalysis-based gamification intervention, embedded in the daily workflow of software practitioners via Jira and Hubstaff, can function as a technology-supported workplace learning environment to improve learning productivity in RCM. Rather than treating gamification as an external add-on, the intervention was designed as an integral part of work-integrated learning, in which real RCM tasks simultaneously serve as production activities and situated learning experiences. The quasi-experimental ABA design enabled systematic observation of behavioral and process changes before, during, and after the intervention.

Empirically, the findings show that the intervention increased task completion collaborative participation in issues, and interaction intensity with work tools during the gamification phase. Still, most of these gains diminished after reinforcement was withdrawn. A notable exception emerged in task completion time efficiency, which continued to improve in the retention phase, suggesting that some aspects of process learning and workflow standardization were internalized and sustained beyond the presence of gamified stimuli. Regression analyses further highlighted the dominant contribution of Unpredictability & Curiosity (CD7) and Social Influence & Relatedness (CD5) support from Epic Meaning & Calling (CD1) and, in specific cases, Loss & Avoidance (CD8), across the four learning productivity indicators.

Theoretically, this study extends the literature on gamification and professional learning by mapping effects at the level of specific motivational drivers rather than treating gamification as a homogeneous instructional package. The identification of CD7 and CD5 as consistent predictors of collaboration, activity intensity, and completion output refines current understandings of how game-based elements can be aligned with technology-supported workplace learning models to sustain engagement, social relatedness, and purposeful challenge in complex, team-based tasks. The differentiated retention patterns between structural indicators (time efficiency) and social-behavioral indicators (collaboration and activity) further suggest that designs should combine short-term motivational levers with long-term process-oriented learning goals.

From a practical perspective, the results offer concrete guidance for educators, learning designers, and organizational leaders seeking to use gamification to support continuous learning in software development settings. Embedding role-based narratives, transparent progress visualizations, and socially visible recognition mechanisms into existing tools enables seamless integration of learning activities into everyday work, while log data from Jira and Hubstaff can be used to iteratively calibrate missions and incentives to sustain engagement is sustained without causing fatigue. In the broader context of information and education technology, this study demonstrates that productivity-oriented metrics, such as task completion rate, collaborative engagement, activity duration, and completion time, can serve as significant indicators of learning productivity when examined from a work-integrated learning perspective. Future research may extend this model to different organizational contexts and complement log-based indicators with more direct measures of knowledge growth, error reduction, and self-regulated learning to further clarify how gamified, data-driven environments can foster sustainable professional development for software practitioners.

ETHICAL APPROVAL

Inclusion criteria comprised active use of Jira in unit projects for at least three months before the study, continuous connection to Hubstaff during working hours, membership in the team's Kanban workflow, and willingness to participate in all study phases. All participants provided written informed consent; data were pseudonymized at extraction and analyzed in aggregate. Institutional ethical approval was obtained from the ITS ethics committee (Ref. 2816/IT2.IX.8/T/TU.00.08/VIII/2025).

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Denny Sagita Rusdianto led the conceptualization and methodological design of the study, conducted validation and formal data analysis, prepared the original draft of the manuscript, managed the project, and developed the visualizations. Umi Laili Yuhana contributed to the conceptualization and methodology, supported validation activities conducted the investigation, and was primarily responsible for supervision, critical review, and editing of the manuscript. Hadziq Fabroyir contributed to the conceptualization and methodological refinement, supported validation, provided key resources, and supervised the research and contributed to the review and editing of the manuscript. All authors have read and approved the final version of the manuscript.

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