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The AI–Gamification Integrated HR Control (AGIHC) Model: A Conceptual Framework for Employee Selection and Placement in Indonesia

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ABSTRACT

Purpose – Selection and placement in many organizations remain subjective and inefficient, while gamification's engagement potential is rarely applied to hiring. This study explains why an integrated approach is needed and proposes the AI–Gamification Integrated HR Control (AGIHC) Model, which couples AI as an analytic engine with gamification as an engagement interface to optimize the HR control system in an emerging-market (Indonesian) context.
Methods – A Design Science Research approach was combined with a structured narrative synthesis of Scopus- and Sinta-indexed literature (2020–2026). The model was developed as a designed artifact, with a mixed-methods validation roadmap specified for the next phase.
Findings – Based on the synthesized literature rather than on primary measurement in this study, individual primary studies report reductions in time-to-hire and cost-per-hire on the order of one-third; this figure is taken from those cited studies and is not an average computed in the present synthesis. Only 7.3% of gamification studies address recruitment versus 85.4% targeting existing employees. The resulting AGIHC Model specifies three layers: an Input Layer (AI screening plus gamified assessment), a Process Layer (AI matching plus gamified onboarding), and an Output Layer (AI analytics plus a gamified dashboard).
Research implications – As a conceptual contribution, the propositions await empirical testing, and the single-country Indonesian framing bounds generalizability. Deployment also depends on data governance, candidate consent, and the explainability of AI scoring.
Originality – The study bridges two previously parallel literatures in an integrated AI–gamification HR control framework and provides testable propositions for engagement-driven, fairness-aware selection and placement.

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INTRODUCTION

Digital transformation has reconfigured the function of human resource management (HRM), with recruitment emerging as one of the most prominent areas of AI adoption [1], [2]. In Indonesia, this transformation is supported by the National Strategy for Artificial Intelligence 2020–2045. Nevertheless, organizational readiness remains uneven. Among 73 benchmarked economies, Indonesia is classified as a "rising contender," indicating substantial development potential but relatively limited current AI exposure [3]**.** This challenge reflects a broader global readiness gap, as only 13% of organizations were assessed as fully prepared to deploy AI [4] , despite approximately half of employees worldwide already using AI weekly [5]. Recruitment frequently serves as an organizational entry point for AI adoption; evidence from US organizations indicates that 64% identified recruitment as a leading HR use case for AI in 2025 [6]. However, in many organizations, employee selection and placement remain subjective, labour-intensive, and insufficiently data-driven, creating continuing risks of mis-hiring and biased decision-making.

At the global level, the value proposition of AI in recruitment is increasingly quantifiable. Individual primary studies report reductions of roughly one-third in time-to-hire and cost-per-hire when AI is deployed across the sourcing, screening, and scheduling pipeline, alongside improvements in screening throughput; these are magnitudes reported in the cited studies rather than a pooled average computed here [7]. These efficiency gains, however, coexist with documented concerns about algorithmic bias, procedural fairness, and low candidate trust, which can erode the legitimacy of selection decisions if left unmanaged [8], [9]. This tension frames the central design imperative of the present study: AI should augment rather than replace human judgment, and its analytic power should be paired with mechanisms that preserve a fair and engaging candidate experience.

Scholarship on AI in recruitment and selection (R&S) has matured quickly. Systematic reviews position R&S as the backbone of HRM and the most prominent locus of AI integration [1], while the advent of generative AI has intensified both opportunity and uncertainty for the HR profession[2]. Empirical studies confirm tangible gains in screening efficiency and a partial reduction of unconscious bias [7], [10], and broader reviews document transformation across talent acquisition, learning, and performance management [11]. Interdisciplinary syntheses caution, however, that the field remains fragmented and that adoption outcomes hinge on organizational and data conditions rather than on the technology alone[9], [12].

A second stream concerns algorithmic fairness. Evidence on diversity, equity, and inclusion underscores a dual effect: AI can promote fairness yet also reproduce embedded bias, as illustrated by well-known cases in which historical training data penalized particular groups [9], [13], [14]. This literature increasingly calls for fairness-by-design, transparency, and human oversight, considerations that acquire legal force in Indonesia under Law No. 27 of 2022 on Personal Data Protection [15]. Fairness and data governance are therefore not peripheral but constitutive requirements of any AI-enabled selection system.

A third stream examines gamification in HRM. Self-determination theory (SDT) is the dominant theoretical lens, framing gamified elements as satisfiers of the basic psychological needs for autonomy, competence, and relatedness, thereby strengthening intrinsic motivation and engagement [16], [17]. Meta-analytic evidence indicates that gamification produces, on average, small-to-moderate positive effects on cognitive, motivational, and behavioral outcomes, with effects contingent on design quality rather than on the mere presence of game elements [18]. Points, badges, and leaderboards (PBL) remain the most frequently applied mechanics, and empirical and review evidence, including Indonesian studies, associates gamified HR practices with higher engagement and assessment participation [19], [20], [21], [22]. Critically, however, application to hiring is thin: across recent Scopus-indexed corpora only 7.3% of gamification studies address recruitment, whereas 85.4% target existing employees [23].

To integrate these streams, this study adopts a triangulated theoretical framework. First, algorithmic-HRM and technology-acceptance perspectives explain the conditions of adoption, locating success in organizational readiness and the digital competence of the HR function[12].

Second, SDT explains the motivational mechanism through which gamified assessment elicits engagement and richer behavioral data [16]. Third, organizational control theory provides the governance logic: following the classic distinction among input, behavior, and output control and the cybernetic principle of feedback regulation [24], selection, placement, and monitoring can be conceived as an integrated control system rather than as discrete events. Together these lenses answer three complementary questions: whether the system is adopted, why users engage, and how engagement is converted into governable performance.

Despite their complementarity, these literatures have evolved in parallel. AI supplies analytic power but, used alone, risks an opaque and potentially biased process that diminishes candidate experience. Gamification supplies engagement and behavioral signal but is rarely applied to selection and typically lacks predictive-analytic rigor. No widely validated framework treats AI as the analytic engine and gamification as the engagement interface within a unified HR control architecture that links selection to placement and to ongoing performance monitoring. This integration gap is compounded by an empirical gap: emerging-market organizations, including those in Indonesia, are under-represented in the evidence base despite facing distinctive readiness, infrastructure, and regulatory conditions.

Integrating the two technologies is mutually reinforcing. Gamified assessment generates granular, behavior-based data that improve the training signal available to machine-learning models while enhancing the candidate experience; reciprocally, AI confers predictive validity and continuous bias-monitoring on gamified competency scores. Embedding both within an input-process-output control system connects front-end selection to downstream placement and performance governance, transforming hiring from an isolated event into a controllable, data-informed subsystem of talent management. Situating this design in the Indonesian context responds to documented adoption gaps and to the developmental aim of strengthening locally grounded research and managerial capacity in emerging-market organizations.

Accordingly, this study proposes and theoretically develops and justifies the AI-Gamification Integrated HR Control (AGIHC) Model. Its objectives are to: (1) analyze the effectiveness of AI in employee selection and placement; (2) examine the role of gamification in enhancing engagement and the accuracy of competency assessment; and (3) develop an integrated AGIHC model to optimize the HR control system. Three theory-grounded propositions guide the model. **P1**: AI-based screening improves the efficiency and predictive validity of selection (technology-acceptance and analytics logic). **P2**: gamified assessment increases candidate engagement and the richness of competency data through the satisfaction of autonomy, competence, and relatedness (SDT logic). **P3**: integrating AI and gamification within an input-process-output control architecture improves the effectiveness of selection, placement, and performance monitoring relative to non-integrated approaches (control-theoretic logic).

To make these propositions testable, the study defines the comparison and the primary outcomes in advance. The integrated condition is the full AGIHC configuration, in which AI screening, gamified assessment, and the closed performance-feedback loop operate together; the non-integrated comparators are conventional AI screening without gamified assessment and gamified assessment without an analytic engine, run in parallel with the incumbent process. The primary outcome for P1 is the incremental criterion-related validity of screening, with time-to-hire as a secondary process outcome; for P2 it is the candidate assessment-completion rate together with perceived procedural fairness and engagement; and for P3 it is placement quality and early (six- to twelve-month) turnover. Effect-size thresholds, the follow-up window, and the decision criteria for confirming or disconfirming each proposition will be pre-registered before the pilot, so that the propositions are tested rather than merely illustrated.

METHOD

Research design

This is a conceptual, theory-building study conducted through a Design Science Research (DSR) logic, in which the principal output is a purposefully designed artifact, the AGIHC Model, that is derived from and justified by a structured narrative synthesis of recent literature [25], [26]. The DSR orientation is complemented by a planned mixed-methods validation roadmap consistent with established methodological guidance [25], [26]. The present article reports the problem-identification, knowledge-synthesis, and artifact-design phases; empirical evaluation is specified as the subsequent phase of the funded research programme.

The choice of DSR is deliberate rather than incidental. Selection and placement constitute a class of organizational problems for which purely explanatory research is insufficient: the phenomenon of interest does not yet exist in a stable form that can be observed, because integrated AI–gamification hiring systems are still rare in practice. DSR is designed precisely for such situations, since its epistemic contribution is prescriptive knowledge, that is, knowledge about how an artifact should be constituted so that it reliably produces a desired outcome in a defined class of contexts. The present study therefore follows the canonical DSR cycle of problem identification and motivation, definition of the objectives of a solution, design and development, demonstration, evaluation, and communication, and reports the first three activities in full while specifying the remaining activities as an executable agenda [26].

Rigour in a conceptual DSR study is secured through three mechanisms. First, the design is derived from, and traceable to, an explicit knowledge base: every structural element of the model is anchored in at least one peer-reviewed source and at least one theoretical mechanism, as documented in the theoretical mapping presented in the results. Second, the design is expressed as falsifiable propositions rather than as an open-ended prescription, so that the artifact can be disconfirmed by subsequent evidence. Third, the design requirements are stated at a level of abstraction that allows instantiation in different organizational settings without prescribing a single proprietary technology, which protects the framework from rapid obsolescence as specific tools change. Relevance, in turn, is secured by grounding the problem statement in documented adoption gaps in the Indonesian context rather than in a purely academic puzzle.

Participants

Because this phase is conceptual, it involves no human participants. The planned validation phase will engage two groups: (a) an expert panel of HR practitioners and AI/data-science specialists for content-validity assessment of the model, and (b) candidates and HR officers at partner organizations in Indonesia for a limited pilot implementation.

The expert panel is planned to comprise between eight and twelve experts, a range consistent with conventional guidance for content-validity assessment, and will be composed to balance three competencies: human-resource practice (senior recruiters and HR managers with at least five years of selection experience), technical competence (data scientists or machine-learning engineers with applied experience in predictive modelling), and academic competence (scholars publishing in HRM, industrial-organizational psychology, or information systems). The pilot phase will recruit candidates and HR officers from partner organizations through their ordinary recruitment cycles, so that the gamified assessment substitutes for, rather than adds to, the existing selection burden. Participation will be voluntary, informed consent will be obtained before any data processing, and candidates who decline the gamified route will be offered an equivalent conventional assessment so that no applicant is disadvantaged by the research.

Population, sampling, and instrumentation

The synthesis reported in this article is completed work, and its evidentiary base is a corpus of peer-reviewed, Scopus- and Sinta-indexed articles published between 2020 and 2026, retrieved from Scopus, Web of Science, and Google Scholar using keyword strings combining artificial intelligence, recruitment/selection, gamification, employee engagement, and HR control system. Inclusion criteria required a workplace or HRM focus, peer-reviewed status, and direct relevance to selection, assessment, or control; seminal systematic reviews were purposively prioritized, and non-peer-reviewed or off-topic items were excluded. The elements described from this point onward belong to the planned pilot, which has not yet been conducted. For that pilot, instrumentation will comprise an expert content-validity rubric, a gamified competency-assessment battery operationalized through PBL mechanics, a machine-learning screening pipeline, and a validated work-engagement scale. Psychometric adequacy will be established before deployment, with target thresholds of Cronbach's alpha of at least 0.70 for internal consistency and an item content-validity index (or Aiken's V) of at least 0.80 for content validity.

The literature search was conducted in three passes. The first pass applied the keyword strings to titles, abstracts, and keywords and yielded a broad candidate set; the second pass screened titles and abstracts against the inclusion criteria, removing duplicates, non-workplace applications (principally gamified education studies without an HRM outcome), and items whose treatment of AI was purely technical with no organizational referent; the third pass read the retained items in full and extracted, for each, the construct addressed, the mechanism proposed, the empirical outcome reported, and the stated limitation. Seminal works outside the 2020–2026 window were retained only where they constitute the theoretical foundation of a construct used in the model, which is why the classic formulation of organizational control is cited despite its earlier publication date [24]. The extracted material was coded thematically into three clusters, corresponding to the analytic, motivational, and governance streams that the model subsequently integrates. Screening and thematic coding were carried out independently by the first two authors; disagreements were resolved by discussion and, where necessary, adjudicated by the senior author, and each retained study was appraised for methodological adequacy in design, sample, and outcome measurement, with only studies meeting a minimum adequacy threshold admitted to the synthesis.

The strings applied to title, abstract, and keyword fields were: ("artificial intelligence" OR "machine learning" OR "algorithmic HRM") AND ("recruitment" OR "selection" OR "hiring" OR "employee placement"); ("gamification" OR "game-based assessment" OR "serious game") AND ("human resource*" OR "employee engagement" OR "competency assessment"); and ("organizational control" OR "HR control system" OR "performance monitoring") AND ("human resource management" OR "talent management"). Because the objective was theory construction rather than effect estimation, the review was conducted as a structured narrative synthesis and is reported as such, not as a systematic review; per-stage record counts were not logged prospectively, so no PRISMA flow is claimed. What can be reported precisely is the resulting evidentiary base. Nineteen peer-reviewed journal articles and conference papers were retained from the keyword searches. These were supplemented by three foundational theoretical and methodological sources located through citation chaining ([24], [25], [26]), and by six industry, statistical, and regulatory documents used solely for contextual indicators and not as part of the theoretical synthesis ([3], [4], [5], [15], [27], [28]). Screening proceeded iteratively against the criteria above, and the stopping rule was thematic saturation rather than exhaustiveness: searching continued until further records returned mechanisms already represented within the three streams. The absence of prospective stage counts is acknowledged as a limitation of the synthesis, and any subsequent attempt to estimate effect sizes rather than to construct theory would require a full PRISMA-compliant protocol registered in advance.

Instrumentation for the planned pilot is specified in advance to reduce researcher degrees of freedom. The gamified competency battery will operationalize points, badges, and leaderboards as the visible mechanics, but the scored constructs will be behavioural rather than cosmetic: task persistence, accuracy under time pressure, decision consistency, and collaborative behaviour in a simulated team task. The AI screening pipeline will be trained on historical hiring and performance data supplied by partner organizations, with protected attributes excluded from the feature set and retained separately for fairness auditing only. Engagement will be measured with a validated work-engagement scale, and perceived procedural fairness will be measured with an established organizational-justice instrument, since candidate trust is a stated design objective and must therefore be observable [8], [13].

Procedures and time frame

Development proceeds in five stages aligned with the grant timeline: (1) needs analysis and preliminary study; (2) model and system-architecture design; (3) prototype development applying machine-learning algorithms for data analysis and gamification elements (points, badges, leaderboards) for competency assessment; (4) limited implementation and pilot testing at partner organizations; and (5) evaluation, refinement, and dissemination.

Each stage carries a defined deliverable and an internal quality gate. Stage one produces a documented problem statement validated against practitioner interviews at the partner organizations; stage two produces the model and its system architecture, which is the deliverable reported in this article; stage three produces a working prototype whose screening component must meet a pre-registered minimum classification performance before it is exposed to any live candidate; stage four produces pilot data from a limited implementation, run in parallel with the incumbent selection process so that the two can be compared without exposing applicants to an unvalidated system as their sole assessment; and stage five produces the refined artifact, the empirical evaluation, and the dissemination outputs. The parallel-run design in stage four is a deliberate ethical safeguard as well as a methodological one, since it permits estimation of incremental validity while preserving the integrity of the organization's actual hiring decisions.

Analysis plan

The synthesis phase uses qualitative thematic analysis to extract constructs, mechanisms, and design requirements. The planned evaluation phase will employ descriptive statistics; classification metrics (precision, recall, and area under the ROC curve) for the AI screening component; correlation between gamified competency scores and subsequent job performance to estimate criterion-related validity; paired pre/post comparisons of time-to-hire and cost-per-hire; and partial least squares structural equation modeling (PLS-SEM) to test the relationships implied by propositions P1-P3.

The fairness component of the analysis warrants separate specification, because a screening model that is accurate in aggregate may nevertheless be inequitable across subgroups. The evaluation will therefore report disaggregated performance and at least two formal fairness criteria, namely demographic parity in selection rates and equalized odds in true-positive and false-positive rates across protected groups, alongside an explanation layer that renders individual scores interpretable to both recruiters and candidates. Where these criteria conflict, as they frequently do, the resolution will be made explicit and justified rather than concealed in the modelling pipeline, in keeping with the fairness-by-design commitment that motivates the model [13], [14]. For the PLS-SEM component, the minimum sample size will be determined by inverse-square-root power analysis for the most complex construct in the model, and measurement quality will be assessed through composite reliability, average variance extracted, and the heterotrait–monotrait ratio before any structural path is interpreted. In addition, because the gamified format may itself disadvantage some candidates, the evaluation will include accessibility testing for candidates with disabilities, neurodivergence, older age, limited gaming familiarity, lower device quality, or restricted digital access, and will assess measurement invariance across these groups before any competency score informs a selection decision.

Because the present phase produces an artifact rather than an estimate, its quality criteria are those of design rather than of inference. Internal consistency is assessed as the coherence between the stated problem, the theoretical mechanisms invoked, and the structural elements of the model; each layer of the architecture must be traceable to a mechanism, and each mechanism to a proposition. External validity is bounded and stated rather than claimed, and the boundary conditions are made explicit in the discussion. Ethical adequacy is treated as a design constraint rather than a compliance afterthought: the model is specified so that candidate data are collected for a declared purpose, retained for a defined period, and processed with human oversight over every consequential decision, in line with the requirements of Law No. 27 of 2022 on Personal Data Protection [15]. Ethical clearance from the institutional review board will be obtained before the pilot phase begins.

As a conceptual contribution, the study does not yet report empirical outcomes; the propositions remain to be tested. Generalizability is bounded by the single-country (Indonesian) framing and by the selected literature window. These constraints are revisited in the discussion and translated into a concrete validation agenda.

RESULTS AND DISCUSSION

Results

The principal result is the AI-Gamification Integrated HR Control (AGIHC) Model, a three-layer architecture that maps the talent-acquisition lifecycle onto the input-process-output logic of an organizational control system[24]. In the Input Layer, AI-driven screening parses and ranks applicants while a gamified assessment captures competency- and behavior-based signals; jointly these constitute input control, standardizing and enriching the pool that enters the system. In the Process Layer, AI person-job matching aligns validated profiles with role requirements while gamified onboarding supports adaptation; this constitutes behavior/process control over placement quality. In the Output Layer, AI analytics and a gamified performance dashboard provide continuous monitoring; this constitutes output control and closes a cybernetic feedback loop in which realized performance is fed back to recalibrate screening criteria and assessment design. Table 1 specifies the layers, and Figure 1 renders the same architecture schematically, with the feedback path drawn explicitly.

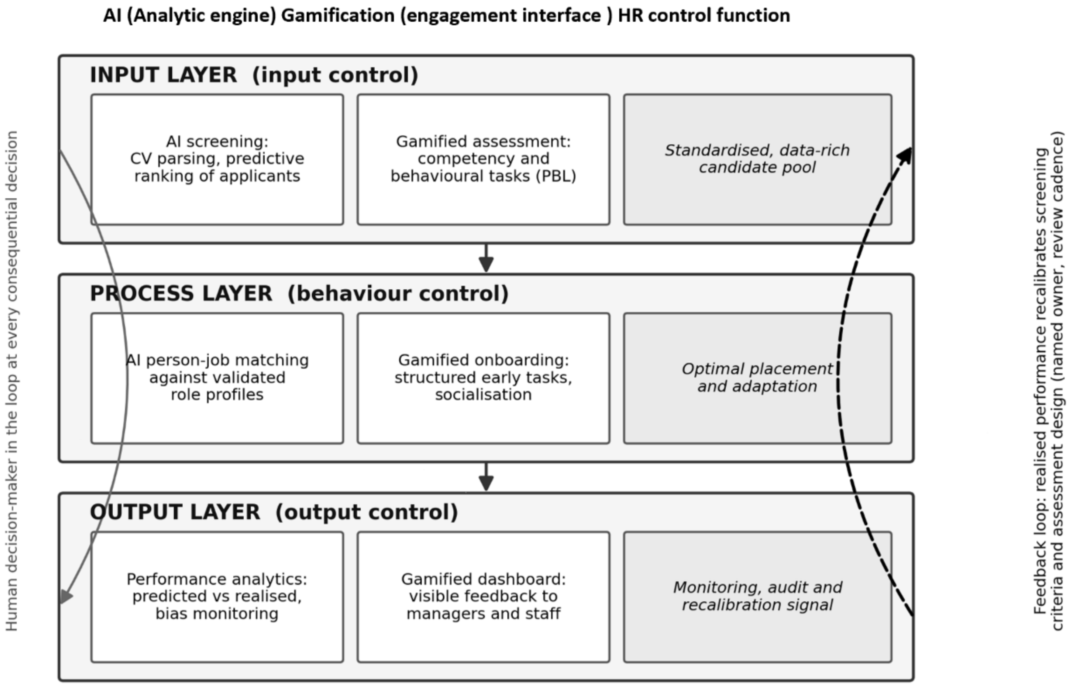

Figure 1. Schematic of the AGIHC Model: three control layers, paired AI and gamification components, and the closed feedback loop from realized performance back to screening criteria and assessment design.

The Input Layer performs two operations that are conventionally separated. The AI component ingests unstructured application material, normalizes it into a structured competency vector, and ranks applicants against a role profile, thereby removing the variance that arises when different recruiters read the same curriculum vitae differently. The gamified component then exposes shortlisted applicants to a series of task-based challenges whose scoring is behavioural: what the candidate does under defined conditions, rather than what the candidate claims to have done. The joint output of the layer is a candidate record that is simultaneously more standardized and richer than the record produced by either component alone, which is the precise sense in which the layer exercises input control over the system boundary[24].

The Process Layer converts that record into a placement decision. Matching is performed against validated role profiles rather than against the historical profile of previous incumbents, a distinction that matters because incumbent-based matching is the mechanism through which historical bias is most commonly reproduced [14]. Gamified onboarding then supports the newly placed employee through structured early tasks that both accelerate socialization and generate an early behavioural signal about fit. This is behaviour control in the classical sense: the layer does not merely record what happens after placement, it shapes the process by which the new employee becomes productive.

The Output Layer closes the loop. Performance analytics compare realized job performance against the competency profile predicted at selection, and the resulting discrepancy is the primary learning signal of the whole system: where predicted and realized performance diverge systematically for a particular role or a particular subgroup, the screening criteria and the assessment design are recalibrated. A gamified dashboard renders this feedback visible to managers and, in a suitably anonymized form, to employees. The architecture is therefore cybernetic rather than linear; hiring ceases to be a terminal event and becomes a regulated subsystem whose parameters are continuously updated by the performance it produces.

Read as a whole, the architecture implies five design requirements that any faithful instantiation must satisfy. First, behavioural data generated by gamified assessment must feed the analytic engine rather than sit in a parallel repository, since the integration claim of the model rests on this coupling. Second, every consequential decision must retain a human decision-maker in the loop, so that the system augments rather than replaces judgment. Third, the model must expose an explanation for individual scores. Fourth, protected attributes must be excluded from the feature set but retained for auditing. Fifth, the feedback path from realized performance back to screening criteria must be an implemented pathway with an owner and a review cadence, not an aspiration. These requirements are the practical content of the framework, and they are what distinguishes it from a mere assemblage of tools.

Because the output layer feeds realized performance back into future screening, the feedback loop is itself a potential source of harm: historical hiring and performance labels may encode past discrimination, biased supervisor ratings, occupational segregation, and unequal opportunity, and excluding protected attributes does not prevent correlated proxy features from reproducing these patterns. The framework therefore treats the loop as a governed rather than an automatic process and specifies six controls: label-bias assessment of historical outcomes before any label is used for training; proxy-feature analysis to detect residual demographic correlation; dataset-shift monitoring to detect drift between the training and deployment populations; subgroup calibration with disaggregated error reporting; mandatory human review of any feedback-driven change to screening criteria; and a prohibition on unattended automatic retraining. Authority to approve a recalibrationrests with a named data-governance owner, who may act only on documented evidence that the change improves subgroup-level fairness and validity, and every change is logged and reversible. These controls are design requirements rather than optional add-ons, and their omission places an instantiation outside the model.

Table 1. Architecture of the AGIHC Model

Layer / control type	AI component (analytic engine)	Gamification component (engagement interface)	HR control function
Input (input control)	CV parsing and predictive screening and ranking of applicants	Gamified competency and behavioral assessment (PBL)	Standardized, data-rich candidate selection at the system boundary
Process (behavior control)	AI person-job matching from validated profiles	Gamified onboarding and early socialization	Optimal placement and adaptation of selected candidates
Output (output control)	Performance analytics and continuous bias monitoring	Gamified performance dashboard and feedback	Monitoring and feedback loop that recalibrates earlier layers

Beyond the artifact, the synthesis consolidates three empirical anchors that justify the design. First, AI substantially compresses recruitment cycle time and cost, with individual primary studies reporting reductions on the order of one-third in time-to-hire and cost-per-hire and material gains in screening throughput [7], [10]. Second, the engagement potential of gamification is well documented yet under-exploited in hiring, where only 7.3% of studies operate [23], [29] and where meta-analytic effects are positive but design-contingent [18]. Third, SDT supplies the mechanism linking gamified design to engagement and to the generation of richer assessment data[16], [17]. The components are therefore individually effective but have not been combined into a controllable selection-to-performance system. Table 2 maps each theoretical lens to its mechanism, its corresponding AGIHC element, the relevant proposition, and key sources.

The two headline figures merit interpretation rather than mere restatement. The approximately one-third reduction in time-to-hire and cost-per-hire indicates that the efficiency case for AI in recruitment is essentially settled at the level of process metrics [1]. What it does not establish is that the quality of the resulting hires improves, because time-to-hire and cost-per-hire are throughput measures and say nothing about criterion-related validity. The asymmetry between the 7.3% of gamification studies addressing recruitment and the 85.4% addressing incumbent employees is equally telling: it reveals that the engagement literature has concentrated where the population is captive and measurement is easy, and has largely avoided the setting in which engagement is most consequential and most fragile, namely the point at which an applicant decides whether to complete an assessment at all [23], [29]. The AGIHC Model is positioned precisely in that under-populated intersection, and this positioning, rather than the novelty of either component, is its principal claim to contribution. Both figures are drawn from individual primary studies and are reported here as they appear in those sources; because the present review is narrative rather than meta-analytic, they are not pooled into a single estimate, and the dispersion across heterogeneous studies, populations, and role types is itself a reason to treat the propositions as testable rather than settled.

Table 2. Theoretical mapping of the AGIHC Model

Theoretical lens	Mechanism	AGIHC element	Proposition	Key sources
Algorithmic HRM / technology acceptance	Adoption via organizational readiness and digital competence	AI screening and matching	P1	[1], [9], [12]
Self-determination theory	Autonomy, competence, relatedness drive engagement	Gamified assessment and onboarding	P2	[16], [17], [18]
Organizational control theory	Input, behavior, and output control with feedback	Three-layer control architecture	P3	[24]

Discussion

The AGIHC Model resolves the analytics-engagement tension that characterizes contemporary digital HRM. Where AI alone risks opacity and bias, the gamified interface humanizes the candidate experience and generates behavior-based signals; where gamification alone lacks rigor, the AI layer supplies predictive validity and continuous fairness monitoring. The design is theoretically triangulated rather than additive: technology-acceptance logic explains whether the system is adopted, SDT explains why gamified elements sustain engagement, and control theory explains how engagement is converted into governable performance through input-process-output regulation. This triangulation distinguishes AGIHC from single-lens treatments that examine AI or gamification in isolation and from practitioner toolkits that bundle features without an explicit control logic.

Comparison with prior work sharpens this claim. Systematic reviews of AI in recruitment converge on efficiency gains coupled with unresolved ethical exposure, and they consistently conclude by calling for frameworks that operationalize fairness rather than merely diagnose its absence. Empirical studies of AI screening report improved throughput and a partial attenuation of unconscious bias, but they treat the candidate as an object of assessment rather than as a participant whose engagement is itself a variable. Conversely, the gamification literature, including recent Indonesian evidence, documents engagement and participation benefits but stops at the point where those benefits would have to be converted into a defensible selection decision, because it lacks a predictive apparatus. AGIHC differs from both traditions in that it treats the two limitations as reciprocal solutions. The engagement problem of AI is addressed by gamification, and the validity problem of gamification is addressed by AI. The control architecture is what makes the exchange between them explicit.

Two adjacent bodies of work must be ruled out before the integration claim can stand. In learning and development and in performance management, designs that combine analytic or adaptive engines with game elements are already documented [21], [22], which establishes that the pairing of the two technologies is not in itself novel. What those designs do not supply is a control logic. Their feedback terminates in the individual learner's or incumbent's development plan rather than in the selection criterion, and they are never required to defend a hiring decision. Commercially, task- and game-based assessment platforms, among them Pymetrics (now part of Harver), Arctic Shores, and HireVue, likewise bundle behavioural game mechanics with algorithmic scoring, and they demonstrate the technical feasibility of the coupling at scale. They remain, however, point solutions located at the input stage. To the best of the authors' knowledge, none of them specifies as an architectural requirement that realized post-hire performance must flow back to recalibrate both the screening model and the assessment design, under a named owner and a defined review cadence. What is claimed here is therefore not the pairing of AI with gamification, which demonstrably exists, but the closure of the loop across selection, placement, and monitoring.

The model also stands in a definite relation to the meta-analytic evidence on gamification, which reports positive but design-contingent effects. That contingency is not a caveat to be noted and then ignored; it is a direct constraint on the model. If gamified elements are implemented as decorative point-scoring layered over an otherwise conventional test, the self-determination mechanism is not engaged and no additional behavioural signal is generated. The integration then collapses into an ordinary assessment with a scoreboard attached. The propositions should therefore be read conditionally. P2 predicts an engagement effect only where the gamified design satisfies autonomy, competence, and relatedness. P3 predicts a system-level effect only where the behavioural data produced by that design actually enter the analytic engine.

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The model engages directly with the fairness debate. Gamified assessment may, in principle, capture competencies that are less correlated with demographic proxies than conventional resume features, but this is a plausible expectation rather than a demonstrated result and must itself be tested empirically. Gamification is therefore treated here as a double-edged instrument: the same task-based format that can enrich behavioural signal may also introduce new measurement bias linked to disability, neurodiversity, age, prior gaming familiarity, device quality, language, and unequal digital access. Accordingly, the output layer embeds explicit bias monitoring, and the validation plan incorporates accessibility testing and measurement-invariance analysis so that any fairness advantage is established rather than assumed. In the Indonesian setting this is also a compliance question: the processing of candidate data within the model must satisfy the consent, purpose-limitation, and transparency requirements of Law No. 27 of 2022 on Personal Data Protection. Embedding explainability and data-governance controls in the output layer therefore serves both ethical and legal ends, and can convert a potential liability into a source of candidate trust where these safeguards are demonstrated.

The framework also specifies boundary conditions. Its efficacy is contingent on organizational AI readiness and on the digital nativity of the candidate pool, which prior work identifies as a moderator of gamification effects. In low-infrastructure or low-readiness settings, the input layer may need lighter-weight gamification and stronger human oversight, whereas high-readiness organizations can exploit the full feedback loop. Recognizing these contingencies guards against the over-generalization that has limited earlier, context-blind prescriptions.

A further boundary condition concerns role type. The behavioural signals that gamified assessment captures most reliably, such as persistence, decision consistency, and collaborative conduct, map more directly onto operational, technical, and entry-level roles than onto senior positions in which prior track record and professional network dominate the selection criterion. The model is accordingly expected to yield its largest returns in high-volume hiring, where the ratio of applicants to recruiters is unfavourable and the marginal value of standardization is greatest. Returns should be smaller, and may even be negative, in executive search, where the assessment burden imposed on a small number of senior candidates may itself deter application. Stating this scope condition explicitly is preferable to the implicit universalism of much of the practitioner literature.

Implications

Theoretically, the study bridges two previously parallel literatures and reframes selection as a control system, extending organizational control theory into AI-enabled HRM. Practically, it offers HR leaders a sequencing logic for deploying AI and gamification across the hiring lifecycle rather than adopting disconnected point solutions. For policy, it speaks to emerging-market AI strategies by demonstrating how organizations of moderate maturity can capture engagement and efficiency gains while preserving human judgment and legal compliance, aligning with national capacity-building objectives.

The theoretical contribution can be stated more precisely. Organizational control theory was formulated for a world in which measurement was costly and feedback was slow, which is why it distinguishes input, behaviour, and output control as alternative strategies chosen according to the measurability of outputs and the knowledge of the transformation process. Digital instrumentation dissolves part of that trade-off: when assessment is gamified and analytics are continuous, an organization can exercise all three modes simultaneously and at low marginal cost. The AGIHC Model is thus not merely an application of control theory to a new domain but a modest extension of it, proposing that AI-enabled instrumentation converts what was once a choice among control modes into an integrated architecture. Extending self-determination theory into the pre-employment setting is a second theoretical move, since the theory was developed for individuals already inside an institution, whereas an applicant is a volunteer who may exit at any moment and whose autonomy is therefore both more salient and more easily violated.

For practice, the framework implies a sequence rather than a shopping list. An organization should begin with the output layer, because without a defined and measured performance criterion there is nothing against which selection can be validated and no feedback signal to close the loop; it should then implement AI screening in the input layer against that criterion; and only then should it introduce gamified assessment, whose behavioural data become interpretable only once a criterion and an analytic engine exist. This ordering inverts the usual pattern of adoption, in which the visible and marketable gamified interface is procured first and the measurement infrastructure is deferred, and it explains why many such deployments produce engagement without producing better hires. Managers should also budget for the organizational rather than the technical costs of the transition: recruiter roles shift from screening to interpretation and oversight, which requires retraining, and the governance of candidate data requires a named owner with the authority to halt a model that fails an audit.

At the level of policy, the analysis supports a specific reading of Indonesia's national AI strategy. The binding constraint on adoption is evidently not market availability, given the growth trajectory of the domestic AI market, but organizational readiness and capability, as reflected in adoption rates that remain far below market growth. Interventions that subsidize technology procurement are therefore likely to be less effective than interventions that build the data-governance and analytic capability without which procured technology cannot be used well. The compliance architecture created by the personal data protection law should be understood in the same light: as an infrastructure that, if internalized at the design stage, lowers the long-run cost of AI-enabled hiring by making candidate trust a designed property of the system rather than a matter of hope.

The primary contribution is the AGIHC Model itself. Game-based assessment platforms and hybrid designs in adjacent HR domains already combine the two technologies, as discussed above; what the authors have not been able to locate in the published literature or in documented practitioner architectures is a framework that specifies how the two technologies jointly govern selection, placement, and monitoring, accompanied by theory-grounded propositions (P1-P3) and an explicit control logic ready for empirical examination. A secondary contribution is the contextualization of this design for emerging-market organizations operating under data-protection regimes such as Indonesia's. The contribution is conceptual; the propositions are not yet empirically tested, and the single-country framing limits generalizability. Ethical and data-privacy considerations, including candidate consent, transparency, and the explainability of AI scoring, require careful treatment in any deployment and may constrain the model in stricter regulatory environments. Infrastructure and skills constraints common in emerging markets may also affect feasibility.

Three further limitations should be acknowledged. First, the evidentiary base is drawn from indexed literature and therefore inherits its publication bias, most obviously an over-representation of successful implementations, so the efficiency figures cited here should be treated as an upper bound rather than as an expectation. Second, the model presumes a level of data infrastructure, specifically the existence of usable historical hiring and performance records, that many emerging-market organizations do not possess; for such organizations the first phase of implementation is data creation, not model deployment. Third, gamified assessment may itself introduce a form of selection bias, in that candidates differ in their familiarity with and comfort in game-like environments, so the design may inadvertently advantage digitally native applicants. This risk is a direct consequence of the very mechanism that gives the model its engagement advantage, and it can be mitigated through practice rounds and accessible design, but it cannot be assumed away and must be tested empirically. Future work should validate AGIHC through expert appraisal and organizational pilots, estimate effect sizes for engagement and predictive validity, audit the system for algorithmic bias, and conduct longitudinal and cross-cultural replications across sectors and regulatory regimes to assess robustness

CONCLUSION

This study addressed the persistence of subjective, inefficient selection alongside an under-exploited engagement opportunity, and it responds with the AI-Gamification Integrated HR Control (AGIHC) Model. Its central contribution is a testable design proposition: that hiring may be better designed as a closed-loop control system than as a terminal event, with AI serving as the analytic engine, gamification as the engagement interface, and realized job performance as the feedback signal that continuously recalibrates both. The practical significance of that claim lies in the sequence it imposes on managers, which is to define and measure the performance criterion first, to build the analytic layer against that criterion, and only then to introduce the gamified interface. This inverts the prevailing pattern of adoption, in which the visible interface is procured first, and it may help explain why interface-led deployments so often generate engagement without necessarily generating better hires a relationship that itself remains to be tested. The model is offered as a theoretically grounded design awaiting empirical evaluation, and that evaluation, together with fairness auditing under the prevailing data-protection regime, constitutes the next phase of this research programme.

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AUTHOR CONTRIBUTION STATEMENT

SP conceived the study and designed the AGIHC framework; WF conducted the literature synthesis and drafted the manuscript; ES contributed to the methodology and analysis plan; BS supervised the project and critically revised the manuscript. All authors read and approved the final version.

AI DISCLOSURE STATEMENT

The authors used a generative AI assistant on a limited basis, solely to assist with language editing and the mapping of relevant literature. The conception, analysis, interpretation, and substantive arguments of this work are entirely the authors' own. The authors reviewed and verified all AI-assisted output and take full responsibility for the content of the publication.

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