

## Clicking “Save” as a Proxy for Intent: An AI-Driven Conceptual Model of Micro-Commitments in the Talent Funnel

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### Abstract

The digitization of recruitment has transformed talent acquisition into a data-rich, behaviorally traceable process. While most recruitment analytics focus on macro-conversion points such as job applications, interviews, and hiring decisions, emerging digital traces such as clicking “Save” on a job posting represent micro-commitments that may signal candidate intent. Drawing from literature in artificial intelligence (AI), recruitment analytics, behavioral economics, digital marketing, and human-computer interaction, this paper proposes a conceptual AI-driven model that treats micro-commitments as predictive indicators within the talent funnel. The model integrates behavioral signal capture, feature engineering, intent scoring algorithms, and recruiter dashboards to enhance decision-making. The study identifies a research gap in linking early behavioral signals to hiring outcomes and formulates a theoretical framework that repositions “Save” clicks as measurable proxies for intent. The findings suggest that AI-enabled talent systems can enhance funnel efficiency, improve predictive validity, and support bias mitigation when ethically designed. Practical implications for HR practitioners, technology vendors, and researchers are discussed, alongside future research directions.

### Keywords

*Artificial intelligence; micro-commitments; talent funnel; recruitment analytics; applicant tracking systems; candidate intent; predictive modeling; HR technology.*

## **Introduction**

The contemporary recruitment landscape is increasingly characterized by digital platforms, AI-driven analytics, and applicant tracking systems (ATS). Recruitment processes now generate granular behavioral data at every candidate touch point. While traditional talent funnels conceptualize progression through discrete stages awareness, application, interview, offer, and hire digital systems reveal a spectrum of micro-interactions that precede formal application. Actions such as clicking “Save,” bookmarking job postings, revisiting listings, or partially completing applications may represent meaningful psychological commitment.

This paper proposes that such micro-commitments can be modeled as proxies for intent using artificial intelligence. By conceptualizing “Save” as a measurable early-stage commitment, organizations may gain predictive insight into candidate progression and improve recruitment efficiency. The research gap of the study are Lack of conceptualization of micro-commitments in recruitment theory, Limited integration of behavioral trace data into talent funnel models, Absence of predictive frameworks linking “Save” clicks to funnel progression.

This study addresses these gaps by proposing an AI-driven conceptual model of micro-intent. The study builds a conceptual framework that integrates AI-driven predictive analytics with behavioral engagement theory to advance understanding of digital talent funnels.

## **Research Question**

Can micro-commitments such as clicking “Save” on job postings be modeled using artificial intelligence as valid proxies for candidate intent within the digital talent funnel?

## **Review of Literature**

### **1. Artificial Intelligence in Recruitment**

AI technologies in HR aim to enhance efficiency, reduce cost, and improve predictive decision-making (Upadhyay & Khandelwal, 2018). AI systems are increasingly embedded in ATS platforms to automate screening, ranking, and candidate matching (Black & van Esch, 2020). Machine learning models can analyze large volumes of applicant data to detect patterns that correlate with hiring success (Tambe et al., 2019).

Despite their advantages, algorithmic recruitment systems raise concerns regarding transparency, bias, and fairness (Köchling & Wehner, 2020; Raghavan et al., 2020). However, when properly designed, AI can reduce human cognitive biases by standardizing evaluation processes (Bogen & Rieke, 2018).

Most studies focus on macro-decision points (resume filtering, interview prediction). Few consider early behavioral traces preceding formal application.

## **2. Talent Funnel and Recruitment Process Models**

The recruitment funnel conceptualizes candidate progression from awareness to hiring (Breagh, 2013). Digital recruitment has expanded this model by incorporating pre-application behaviors such as website visits, social media interaction, and job board engagement (Chapman & Webster, 2003).

Nikolaou (2021) emphasizes the role of digital platforms in shaping candidate journey experiences. Online recruitment transforms job search into an interactive behavioral process where each action generates traceable data. These digital traces create opportunities for predictive analytics but remain underutilized in academic research.

## **3. Behavioral Economics and Micro-Commitments**

Micro-commitment theory draws from behavioral economics and psychology. The commitment-consistency principle suggests that small actions increase likelihood of larger future actions (Cialdini, 2009). In consumer behavior research, micro-conversions (e.g., wishlist additions) predict purchasing decisions (Järvinen & Karjaluoto, 2015).

Similarly, digital engagement theory posits that low-effort interactions represent cognitive interest and psychological investment (Calder et al., 2009). Clicking “Save” may represent a low-cost signal of job interest, comparable to bookmarking products in e-commerce.

Adapting these principles to recruitment suggests that saving a job posting reflects emerging intent.

## **4. Human–Computer Interaction and Digital Trace Data**

Human–computer interaction (HCI) research emphasizes that digital interfaces capture implicit behavioral cues (Gonzalez et al., 2014). Clickstream analysis has been used to predict user engagement and conversion probability (Bucklin & Sismeiro, 2003).

In recruitment platforms, clickstream analytics can capture time spent on job descriptions, scrolling behavior, revisits, and saves. These behaviors represent measurable signals of engagement. However, translating engagement into intent requires predictive modeling.

## **5. Predictive Analytics and Intent Modeling**

Predictive analytics leverages historical data to forecast future outcomes (Tambe et al., 2019). In marketing, intent modeling uses machine learning to identify users likely to convert (Järvinen & Karjaluoto, 2015).

Machine learning techniques such as logistic regression, gradient boosting, and neural networks can estimate probability of application submission based on behavioral features (Shmueli & Koppius, 2011). These models improve decision support by transforming raw behavior into actionable metrics.

Applying intent modeling to recruitment introduces a novel research direction: using micro-commitments as leading indicators of funnel progression.

## **6. Candidate Experience and Ethical Considerations**

Applicant reactions to AI systems influence organizational attractiveness (Langer et al., 2019). Transparency in algorithmic decision-making enhances perceived fairness (Bogen & Rieke, 2018).

Monitoring micro-commitments must respect privacy norms and data protection regulations. Ethical AI design requires explainability and consent (Köchling & Wehner, 2020). Therefore, micro-intent modeling must balance predictive accuracy with ethical responsibility.

## **Research Methodology**

This study adopts a conceptual research design, synthesizing interdisciplinary literature to develop a theoretical framework. Conceptual research is appropriate when introducing new constructs or integrating fragmented domains.

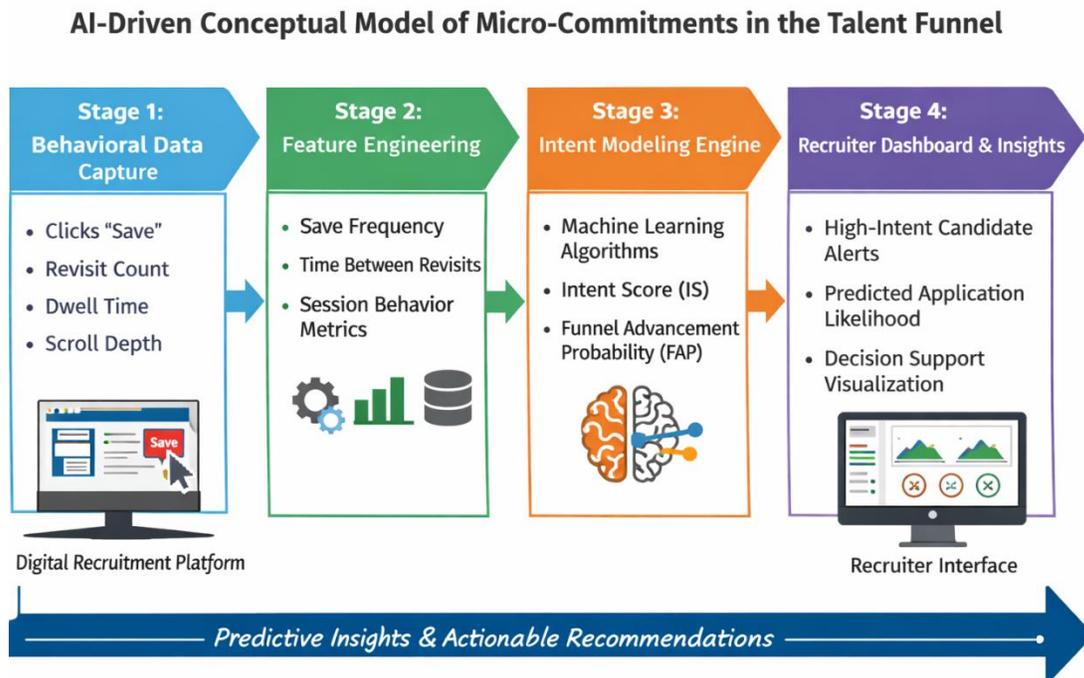


Fig 1 Conceptual Framework

## Conceptual Framework

### Stage 1: Behavioral Data Capture

Digital recruitment platforms capture clickstream and interaction data in real time (Bucklin & Sismeiro, 2003). The “Save” action represents an explicit behavioral marker of interest.

### Stage 2: Feature Engineering

Behavioral signals are transformed into numerical features suitable for machine learning models (Shmueli & Koppius, 2011). For example:

- Binary Save (0/1)
- Time between save and revisit
- Frequency of saved jobs per session

### **Stage 3: Intent Modeling Engine**

Supervised learning models estimate candidate progression probability using historical conversion outcomes (Tambe et al., 2019). Logistic regression or gradient boosting may identify which behaviors significantly predict application submission.

### **Stage 4: Recruiter Dashboard and Decision Support**

Intent scores are visualized within ATS dashboards, enabling recruiters to prioritize high-intent candidates. AI-augmented systems provide recommendations while maintaining human oversight (Black & van Esch, 2020).

### **Findings and Theoretical Contributions**

#### **1. Micro-Commitments Reflect Emerging Intent**

Drawing from commitment theory (Cialdini, 2009), saving a job posting increases psychological attachment. Behavioral economics supports the notion that small actions precede larger commitments.

#### **2. Behavioral Signals Enhance Predictive Validity**

Clickstream features significantly improve prediction models in digital contexts (Bucklin & Sismeiro, 2003). Translating this to recruitment suggests improved forecasting of candidate conversion.

#### **3. AI Reduces Overreliance on Resume-Based Filtering**

Traditional screening emphasizes static resume data, potentially reinforcing bias (Raghavan et al., 2020). Incorporating behavioral signals introduces dynamic indicators of motivation.

#### **4. Improved Funnel Efficiency**

Predictive intent scoring enables proactive engagement strategies. Recruiters can target high-intent candidates before competitors (Nikolaou, 2021).

#### **5. Ethical Guardrails Are Essential**

Algorithmic transparency enhances fairness perceptions (Langer et al., 2019). Behavioral monitoring must comply with data protection standards.

### **Theoretical Contributions**

#### **1. Extends recruitment theory by introducing micro-commitment construct.**

2. Integrates behavioral economics with HR analytics.
3. Advances AI recruitment research beyond resume screening.

Proposes structured operationalization for behavioral trace modeling

### **Suggestions and Practical Implications**

1. Integrate Micro-Intent Analytics in ATS Platforms

Vendors should embed clickstream analytics modules.

2. Develop Transparent Intent Scoring Systems

Recruiters must understand how scores are calculated to maintain trust (Bogen & Rieke, 2018).

3. Pilot Testing and Validation

Organizations should validate predictive accuracy using longitudinal hiring data.

4. Balance Automation with Human Oversight

Hybrid decision models reduce algorithmic overreach (Black & van Esch, 2020).

5. Future Empirical Research

Quantitative studies should test statistical relationships between Save clicks and application rates.

### **Conclusion**

Digital recruitment has evolved into a behaviorally traceable ecosystem where every click generates data. This paper conceptualizes the simple act of clicking “Save” as a measurable micro-commitment that can serve as a proxy for candidate intent. By integrating behavioral theory, AI-driven predictive modeling, and recruitment analytics, the proposed framework extends existing talent funnel models beyond macro-conversion metrics. When ethically designed and transparently implemented, micro-intent modeling can enhance predictive accuracy, improve recruiter efficiency, and refine candidate engagement strategies. Future empirical validation will determine the robustness and generalizability of this conceptual model, potentially redefining how organizations interpret early-stage digital engagement within talent acquisition systems.

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