International Journal of Information Management Data Insights 1 (2021) 100047

Contents lists available at ScienceDirect

International Journal of Information Management Data Insights

journal homepage: www.elsevier.com/locate/jjimei

Artificial Intelligence in Tactical Human Resource Management: A Systematic Literature Review

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A R T I C L E I N F O

Keywords:
Artificial Intelligence
Human Resource Information Systems
Machine Learning
Decision Science
Human Resource Management Systems

A B S T R A C T

Digitization within Human Resource Management (HRM) has resulted in Artificial Intelligence (AI) becoming increasingly prevalent in Human Resource Management Systems (HRMS) and HR Information Systems (HRIS). The tactical procedures of recruitment, employee performance evaluation and satisfaction, compensation and benefit analysis, best practice analysis, discipline management, and employee training and development systems have seen a growth in the incorporation of AI. To better understand this evolution, we seek to explore publication sources and literature that feature the application of AI within HRM. By utilizing a systematic literature review methodology, this paper identifies which tactical HRIS (T-HRIS) components are featured in literature and how each T-HRIS component is represented. This paper gives insight to which component of tactical HRM/HRIS receives attention and identifies gaps in research to give direction to future research agendas.

1. Introduction

Human Resource Management (HRM) modernization has experienced a grand evolution, as digitization infiltrates the tedious processes which exist within its respective operations. From earlier inventions like the computer and the internet, HRM has found a way to navigate these advancements to electronically increase productivity, cost effectiveness, and market competition (Hmoud and Várallyai, 2020). Like a trebuchet, advanced technology launched the rapid evolution of *Human Resource Information Systems* (HRIS) as newer capabilities like Artificial Intelligence began to infiltrate tactical practices within HR operations, otherwise known as tactical HRIS (T-HRIS). The amount of organizational, personnel, and task-orientated data HR is inherently responsible has led to the incorporation of AI in many tactical HR processes, as it enhances sustainable business models (Di Vaio et al., 2020). However, this evolution and growth in capabilities comes with a responsibility of understanding the current state of AI within tactical HR processes, requiring both HR professionals and academics to dive into existing literature which highlights AI-enhanced HR capabilities and areas of growth within the HR discipline.

Literature reviews leading up to this paper have provided a foundational understanding of where Artificial Intelligence exists within HRM and T-HRIS (Di Vaoi et al., 2020; arg et al., 2021a; Qamar et al., 2021; Vrontis et al., 2021). However, these extensive reviews have failed to consider how AI applications are utilized in a managerial and technical standpoint, providing little insight to which components of HRIS are underrepresented with AI capabilities. Identifying this deficiency, we seek to explore this consideration to provide the academic community and professional sector insight to where AI is potentially lacking and where it is thriving. The aim of this research is to explore AI within the HRM and tactical HRIS discipline. Thus, we conduct a systematic literature review (SLR) to provide a baseline to understand the status of T-HRIS components within literature and how it is represented. This SLR, has the objective of identifying and understanding the components of tactical HRIS that are represented most in literature. Within this manuscript, we attempt to bridge this understanding by answering the following research questions: RQ1) What are the tactical HRIS components which exist in published literature? RQ2) How have the components of tactical HRIS been represented in literature?

As a contribution, we seek to inform both the academic community and professional sector with insights to where AI is potentially lacking and where it is thriving. This work scientifically reviews existing literature, identifying what has been accomplished by organizing T-HRIS components on a technical and managerial spectrum. Given the ever-evolving state of technology and newer applications coming to fruition within HRM, the implications of this research are imperative for academics and industry professionals to historically understand the direction research has taken with regards to AI and T-HRIS. This historical understanding will provide insight to potential deficiencies and boons which may exist with regards to AI applications.

The arrangement of this paper is as follows. It first provides a background and framework to tactical HRIS and HRM, the evolution of AI

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https://doi.org/10.1016/j.jjimei.2021.100047
Received 7 September 2021; Received in revised form 3 November 2021; Accepted 7 November 2021

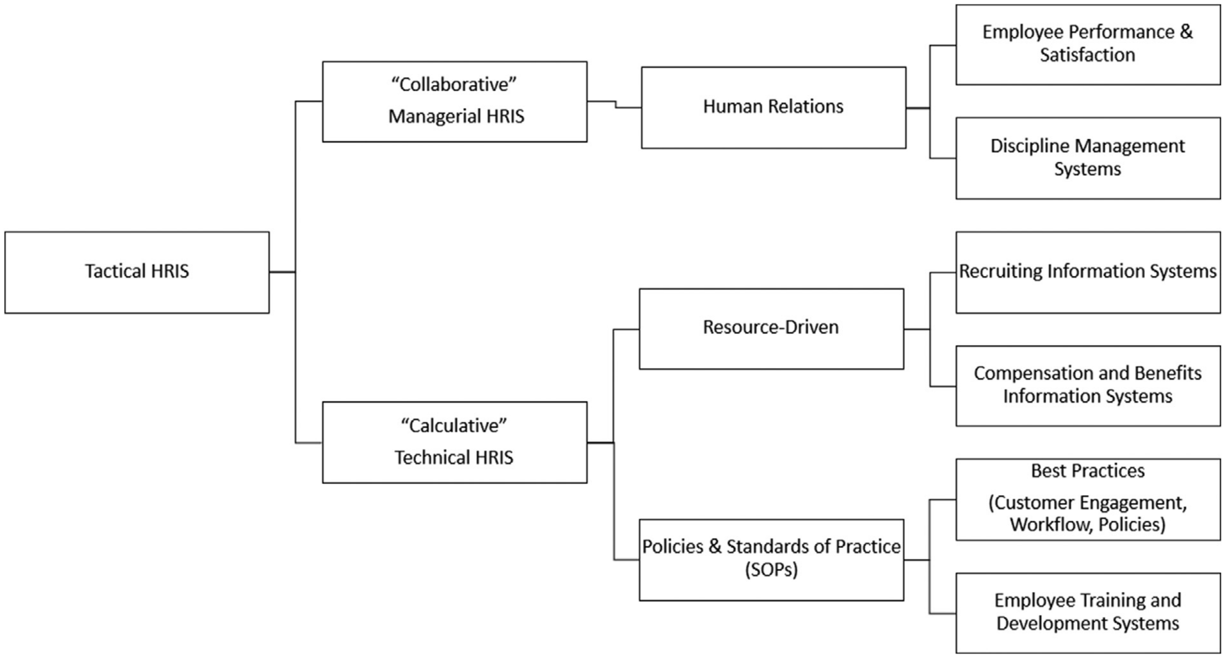


Fig. 1. T-HRIS Framework

within HR, and the AI methods acknowledged in this paper. Secondly, it provides an explanation of the SLR methodology used. Next, it provides the results that include insight to the which components of T-HRIS exist in literature, how they are represented, which publication sources described the research, and future research considerations. Finally, the paper concludes with a discussion of future research opportunities.

2. BACKGROUND AND RELATED WORK OF T-HRIS and AI

Within this section, we define what tactical HRIS is comprised of, propose a framework which outlines the structure of tactical HRIS, identify previous literature reviews which have been conducted in this field, and define common AI methodologies pertaining to this literature review.

2.1. A Tactical Perspective vs. Strategic

Tactical HRIS (T-HRIS) refers to the Human Resource personnel and technology responsible for performing specific tasks inherent to the profession of Human Resource Management to achieve organizational goals and objectives.

T-HRIS equips HR leaders with the technological infrastructure to navigate decisions concerning company best practices, employee performance and satisfaction, recruitment information systems, compensation and benefit information systems, employee training and development systems, and employee discipline management. To understand further, this discipline of HRIS comprises of two separate intellectual assets: managerial HRIS (otherwise known as "soft", "collaborative" and "people-centric") and technical HRIS (otherwise known as "hard", "calculative" and "data-centric") (Collings et al., 2018; Mayfield et al., 2003; Stewart, 2007). Technical HRIS reflects logic, reasoning, data, and understanding. In contrast, the managerial side, is dedicated to relationship building, workplace synthesis and creativity, and the care of the employees who work for the organization (Cregan et al., 2021; Laker and Powell, 2011). To expand upon the structure of T-HRIS, Figure 1 provides a framework outlining the fundamental components which make up T-HRIS (Collings et al., 2018; Kumar, 2012).

2.2. "Collaborative" Managerial HRIS

Managerial human resource management refers to the unique people-centered organizational strengths that contribute to making decisions relating to employee skills, expertise, culture, and commitment (Mayfield et al., 2003; Stewart, 2007). The term "managerial" is about soft skills, which are actions and interactions with others and how we communicate ideas. Connecting these "managerial-skills" with HRIS implies technological capabilities that enable HRM professionals to better connect with employees and effectively make decisions within their respective companies.

At the tactical level, enhancing the information system components of managerial HRM practices improves HRM capabilities by streamlining time-consuming tasks and giving time back to employees and customers alike. Furthermore, managerial HRIS emphasizes the importance of humanizing employee motivation practices to enhance workplace relationships between the organization and its respective employees (Cregan et al., 2021). Two components distinguish the collaborative nature of managerial HRIS. As seen in Figure 1, the first branch of managerial HRIS is the Human Relations component.

2.2.1. Human Relations

The human relations element of managerial HRIS relates to technologies that enhance an organization's ability to generate and maintain professional and effective interpersonal and intrapersonal relationships. Regarding interpersonal relationships, this is an organization's ability to connect and exchange information and ideas between two or more individuals by way of any channel (in person, online, or written) and build relationships (Collinson, 1996; Laker and Powell, 2011). These interactions tend to be in developing relationships and developing an extensive professional understanding on one's organization and those they regularly communicate with (Collinson, 1996).

Similarly, intrapersonal relationships refer to an organization's ability to effectively self-reflect on successes and failures and grow. These interactions tend to be very self-reflective and perceptive to the environment (Laker and Powell, 2011).

The human relations component of T-HRIS provides two components to an organization's ability to manage its employees effectively. The first component is Employee Performance and Satisfaction (EPS), which

Table 1
Tasks within Tactical HRIS "Managerial" Categories

Name	Task Descriptions	Reference
Employee Performance and Satisfaction	Provide performance feedback to employees by tracking employee behavior at work	Tong et al. (2021)
	Assess Employee Productivity	Tong et al. (2021)
	Automate performance evaluations	Tong et al. (2021)
	Generate Personalized Recommendations for Job Improvement	Tong et al. (2021)
	Gauging Workplace Morale	Amer-Yahia et al. (2020); Garg et al. (2021); Rathi (2018)
	Identifying employees who are at risk for leaving	Rathi (2018)
	Identifying when an employee applies him/herself physically, cognitively, and emotionally toward their work	Hughes et al. (2019)
Employee Discipline Management Systems	Fielding harassment claims	Eubanks (2018)
	Regulation of the employment relationship through active intervention in disputes between employers and managers	Jones and Saundry (2012)
	Remain neutral and ensure employees are treated fairly	Bourhis et al. (2019); Jones and Saundry (2012)
	Design policy and procedures for disciplinary actions	Jones and Saundry (2012)
	Enforce disciplinary rules consistently	Jones and Saundry (2012)
	Provide legal guidance to ensure managerial decisions do not lead to expensive litigation	Jones and Saundry (2012)
	Provide broad view of organizational implications of disciplinary actions	Jones and Saundry (2012)

refers to how an organization and its managers connect with its employees, understanding employee diagnostics, and retains talent. This pillar provides insight into how an employee is performing by technologically facilitating performance evaluations and feedback sessions for managers to vector employee behavior and provide them a human connection to discuss successes and concerns within the work environment.

The second component is Discipline Management Systems (DMS) which focuses on employee behavioral rehabilitation and termination processes (Tariq et al., 2016). Regarding DMS, navigating disciplinary issues within an organization requires an in-depth understanding of company policy. However, it also requires strong inter/intrapersonal skills to navigate delicate conversations and potential terminations carefully. Furthermore, connecting with employees and understanding their family demographics to ensure they are correctly being compensated and are receiving the correct benefits is important to the CBA pillar of T-HRIS. Lastly, providing a technological infrastructure that effectively and professionally manages the EPS processes provides both managers and employees more time to communicate and grow within the organization. We provide Table 1 to further define and explore specific task descriptions of these "managerial" categories within T-HRIS to give insight and outline expectations of responsibilities.

2.3. "Calculative" Technical HRIS

Contrary to managerial HRIS practices, "technical" HRIS practices historically have a reputation for reflecting the data-driven and technical skills and capabilities within an organization (Eubanks, 2018; Laker and Powell, 2011). Managerial HRIS centers itself around Human-Relation technologies that help facilitate inter/intrapersonal connections within the organization. Technical HRIS revolves around technologies and information systems that facilitate data analysis, technical understanding, and efficient workflow. This side of the HRIS coin contains two branches that capture the responsibilities within an organization: 1) Resource-Driven capabilities and 2) Policies and Standards of Practice (SOPs).

Whereas managerial HRIS is considered "collaborative" approaches to navigating challenges within an organization, technical HRIS is seen as "calculative" and direct, using data to influence decisions and navigate the challenge of maintaining the competitive edge. Specific categories within technical T-HRIS include customer engagement and workflow Best Practices within the organization, Recruiting Information Systems for talent management, Employee Training and Development systems, and Compensation and Benefits Information Systems which manage an employee's benefits and pay. To further expand on the responsibilities of each category, Table 2 summarizes task descriptions of these "technical" categories within T-HRIS.

2.3.1. Resource Driven

The phrase "resource" alludes to a variety of different ingredients that help propel an organization into success and notoriety. Some examples include allocated budgets, time, technological equipment, and infrastructure. In HRM lens, acquiring and retaining premier talent creates a demand for streamlined HRIS processes to assist in hiring decisions and prevent a company from falling short due to the inability to screen, evaluate, interview, and onboard enough qualified candidates (Ahmed, 2018; Hmoud and Laszlo, 2019).

Furthermore, the pressure of reducing discrimination within the recruiting process and employee compensation/benefits is imperative to maintaining a notable reputation within the industry the organization is a part of (Rathi, 2018). These modern challenges have created a demand signal to bolster these technological capabilities to streamline hiring decision-making processes when acquiring new talent to grow the company. From the technical HRIS perspective, acquiring the employee and retaining them comes first. The managerial practices come later after the asset has been obtained, trained, and put to work.

2.3.2. Policies and Standards of Practice (SOPs)

Company workflow (a measure of employee input and relative output), modernized policies, and logical SOPs create two sub-branches within the second branch of technical HRIS. The first branch sets its attention to Best Practices that exist within an organization. Specifically, this data revolves around employee output relative to the input, customer engagement and satisfaction statistics, policies to reduce administrative burdens, tracking and analyzing employee performance evaluations, and feedback interviews (Eubanks, 2018; Kumar, 2012; Rathi, 2018).

The second branch of technical HRIS sets its focus on analyzing and interpreting employee training and development data. This branch signifies an organization's ability to invest in human capital and bolster assets that already exist within to strengthen retention and further develop their skills. Providing employees with training and education to perform new or hone existing skills can be seen as a return on investment, which this component of HRIS evaluates. Furthermore, this branch statistically identifies deficiencies and knowledge gaps within an organization, prompting training managers to engage more effectively and secure training for those who need it most.

2.4. The Evolution of HRIS

The historical review (Bhuiyan et al., 2014) provides an in-depth insight into the evolution of HRIS. The drastic change in information technology during the 1990s revolutionized HR professionals' roles. Many of the hands-on and analog practices within HRM experienced a great

Table 2
Tasks within Tactical HRIS "Technical" Categories

Name	Task Descriptions	Reference
Best Practices (Customer Engagement/Workflow)	Reduce Administrative Burden	Eubanks (2018)
	Track and Analyzes interviews (feedback) with supervisors and employees	Kumar (2012)
	Track and Analyze input and output of employees	Amer-Yahia et al. (2020); Kumar (2012)
	Track and Analyze positive action guidelines	Kumar (2012)
Recruiting Information systems	Reduce Discrimination within Recruiting Process	Rathi (2018)
	Receive and organize applications for HRM team	Kumar (2012)
	Screen, evaluate, select, onboard prospective candidates	Kumar (2012)
Employee Training and Development Systems	Identifying and personalizing employee professional development options	Obeidat (2012)
	Track employee enrollment of adequate or required training courses related to job	Obeidat (2012)
	Track employee enrolment in courses to develop skill and abilities to carry out new jobs	Obeidat (2012)
Compensation and Benefits Information Systems	Facilitate easy calculations of salaries and wages of employees	Eubanks (2018)
	Ensuring Gender Parity	Eubanks (2018)
	Provide self-services access to payroll system for employees	Muhammad et al. (2021)
	Assist management for salary planning	Muhammad et al. (2021)
	Eases distribution of benefits to employee from management	Muhammad et al. (2021)

deal of technological evolution (Bhuiyan et al., 2014). Punch cards that log an employee's time became digital interfaces that allow employees to use their biometric information to "clock in" to work. Engaging with one's manager or supervisor to request paid-time-off became a simple email rather than a conversation and logging a hand-written calendar. Furthermore, digital job advertisements and applications have become more prevalent in the job market for both the prospective employee and employer.

With the rise of big data and computing capabilities, HRM and HRIS constantly need to cope with the amount of data they receive more effectively. The next frontier of digitization evolution has required incorporating AI within these HRIS functions. HR personnel screening of prospective applicants and their respective resumes can be done by AI applications that utilize fuzzy and neuro-fuzzy-based agent approaches. AI can also create a short list of qualified candidates based on what the HR department is looking for in prospective hires and candidates (Doctor et al., 2009a; Doctor et al., 2009b).

2.5. Reviews of AI within HRM and T-HRIS

There has been recent academic interest in how organizations implement AI within HRM business practices (Abdeldayem and Aldulaimi, 2020; Collins, Dennehy, Conboy, & Mikalef, 2021; Di Vaio, Palladino, Hassan, & Escobar, 2020; Garg, Kiwelekar, Netak, & Ghodake, 2021; Vrontis, Christofi, Tarba, Makrides, & Trichina, 2021). We refer to three systematic literature reviews that have previously investigated AI within HRM (Di Vaio, Palladino, Hassan, & Escobar, 2020; Garg, Sinha, Kar, & Mani, 2021a; Qamar, Agrawal, Samad, & Chiappetta Jabbour, 2021; Vrontis, Christofi, Tarba, Makrides, & Trichina, 2021) and highlight how this work differs from them (see Table 3).

The previous literature reviews that have been conducted regarding AI and HRM practices, although similar in nature, offer very different methodologies and perspectives to consider. For instance, the bibliometric analysis conducted by Di Vaio et al. (2020) reviewed 73 academic articles that met their specified criteria. Specifically, Di Vaio et al. (2020) focused their SLR toward understanding the state of the art of AI and small business models (which included HRM practices) and providing a sense of direction for future research. Whereas, the SLR conducted by Vrontis et al. (2021) analyzed 45 articles and mapped out research of AI within HRM by identifying the broad themes involved (human-robot collaboration, decision-making, learning opportunities, recruiting, training, job performance, and job replacement). The SLR conducted by Qamar et al. (2021) provided insight into the state-of-the-art applications of AI within the HRM domain and sets the stage for a future research agenda. They uniquely developed a taxonomical overview of the AI applications within HRM upon reviewing 59 articles. Lastly, (Garg, Sinha, Kar, & Mani, 2021a) provided a semi-systematic review of 105 articles and identified a strong use of ML applications in recruiting and performance management functions within the HRM spectrum and highlighted the need for HR experts and ML specialists to work together when incorporating the newer AI methodologies within HR practices.

Complementing these three SLRs, this paper studies how AI exists within tactical HRIS (T-HRIS) and HRM practices. We propose a framework that expands the difference between technical T-HRIS (resource and data-driven components) and managerial T-HRIS (human-centric components). Our analysis surveys the last six years of this development (2014-2020), picking up where Bhuiyan et al.'s (2014) survey on the evolution of HRIS left off. Furthermore, it uniquely focuses on AI's application and relationships within tactical components of HRIS and HRM.

2.6. Definitions of Common AI Methods within HRM and T-HRIS

AI uses many analytical methods (Maettig & Foot, 2020). In this paper, we focus on four methods that frequent AI and HRM/HRIS literature. Table 4 provides definitions of the four AI categories.

2.6.1. Machine Learning

"Machine learning" refers to a machine's ability to learn and perform a process given a goal and defined steps (tasks) to train off to reach said goal. A generic example of machine learning within the context of T-HRIS would be training a machine to recommend an employee for promotion. The goal in this example would be the promotion recommendation (the task), and the steps to get there would be the qualifications and criteria weighted against candidates in this decision (the performance metric). Ideally, the training data would be a list of previously recommended employees for promotion and their respective records, contributing to the decision. The machine would then study those tens, hundreds, or thousands of records and identify patterns to recommend given a set of new data (the stimulus/experience) (Mitchell, 2006).

Machine learning also utilizes deep learning techniques, which utilize neural networks (NN) to analyze further and accomplish these complicated recommendation tasks. NN can analyze copious amounts of data quickly and assist humans in recommending business decisions based on analysis completed via NNs (Khan et al., 2020). As an example, such NNs can find correlations between real-life events and sentiment changes via thousands of tweets (from Twitter) and identify topics which

Table 3
Previous AI and HRM Literature Overviews

Authors	Purpose of Literature	Years Included	Number of Primary Studies
Di Vaoi et al.	Comprehensive review of relationship between AI and sustainable business models; identify research gaps between knowledge management systems and AI; implications of AI within sustainable development goals	1990-2019	73
Vrontis et al.	Holistic SLR on AI within HRM practices; understand impact of AI on HRM strategies; understand impact of AI on HRM activities (recruitment and job performance)	unspecified	45
Qamar et al.	SLR of AI and HRM to capture current state-of-the-art and prepare for new research agendas	"as of July 2020"	59
Garg et al., 2021	Semi-systematic literature review; understand current state of ML integration within HRM; showcase relationship between HR experts and ML specialists	2002-2018	105
This Study	Explore Tactical HRIS literature and come to understand which components are exist in literature and how they are further represented.	2014-2020	33

Table 4
AI Methods

Name	AI Descriptions
Machine Learning	The goal is defined and the steps to reach said goal are learned by a machine (training). Uses algorithms and/or deep learning techniques (neural networks) to learn autonomously from data provided and assists by making decisions and providing insights (Khan et al, 2020; Kumar 2019; Ridhwan and Hargreaves, 2021)
Natural Language Processing	Automatic manipulation of natural language such as speech and text. Aims to understand input from human speech as well as generating responses in human languages (Kumar 2019)
Machine Vision	Machine analyses visual information using a camera, analog-to-digital conversation, and digital signal processing. Help computers understand content and context of the world surrounding them. (Kumar 2019)
Recommendation Engines	A tool which provides a personalized recommendation to the user by identifying the right product or content relative to the interactions via any digital channel (Xiao and Benbasat, 2007.)

influenced the sentiment of the public toward events (Ridhwan and Hargreaves, 2021).

2.6.2. Natural Language Processing

Natural Language Processing (NLP) refers to a machine's ability to effectively communicate with humans in their native tongue. Such capability has enabled machines to better understand both speech and text and generate relevant responses to the stimulus it receives from the human.

Such AI practices have become more prevalent when interacting with customers and assisting employees as chatbots and language analysis algorithms have started introducing themselves and streamlining various T-HRIS processes like employee onboarding, recruitment, training, and leave requests (Garg et al., 2021) Majumder and Mondal, 2021). A chatbot can interact with the individual and answer their questions autonomously (Eubanks, 2018; Majumder and Mondal, 2021; Shum et al., 2018).

2.6.3. Machine Vision

Machine vision uses cameras and other sensory devices to provide machines with the ability to process visual data to better understand the world around them and make autonomous decisions based on the received data. Examples of such capabilities are evident in the development and research of self-driving vehicles, medical body-scan technologies in search of cancerous abnormalities at the cellular level, facial recognition systems, and the US Post Office's ability to sort letters containing handwritten addresses (Mitchell, 2006; Rudin, 2019).

Within the context of T-HRIS, machine vision capabilities have started to integrate themselves within recruitment processes and pre-screening interviews. Specifically, the development of a machine "Looking at People" (LAP) is underway. This investigates AI algorithms that review video data to assist in automating the recruitment process by providing HR professions a first impression, personality analysis, and recommending the pursuit of the candidate (Escalante et al., 2017).

2.6.4. Recommendation Engines

Recommendation engines are AI tools that have increasingly infiltrated everyday life in activities ranging from online shopping to find the right playlist of music or podcast to engage. These engines allow companies like Amazon, Facebook, and Netflix to offer personalized experiences to their customers (Xiao and Benbasat, 2007). These unique AI engines highlight content or products that are more likely to appeal to the customers or employees of the company based on behavioral trending data collected on them. The engines also analyze demographic information on the individuals to help connect people via social media websites ("you may also know" functions).

T-HRIS has also seen a growth in these capabilities via candidate recommendations, promotion recommendations, and employee training and development. Recommendation engines not only streamline what once hours of individualized analysis were, but they have empowered HRM professionals with the ability to process copious amounts of data and identify trends that are outside of human capabilities to the computer. These recommendation engines are in action in a variety of publicly accessible applications. For instance, LinkedIn, Instagram, and Facebook are well known for connecting colleagues with one another. LinkedIn serves as a more "professional" social media outlet (think virtual curriculum vitae), Instagram and Facebook cater to the more personal aspects and hobby-based activities in one's life (Papacharissi, 2009; Stapleton et al., 2017).

In summary, this section has provided insight and definitions to tactical HRIS components and showcased a framework which highlights their placement within the structure. We have further explored previous literature reviews which have been accomplished regarding AI applications within HRM and highlighted their purposes, primary citations, and date-range which they cover. Lastly, we have defined AI methodologies with HRM and applicable uses of AI within HRM practices.

3. METHODOLOGY

This section provides a description of the systematic literature review (SLR) process utilized within this study ((Collins, Dennehy, Conboy, & Mikalef, 2021; Di Vaio, Palladino, Hassan, & Escobar, 2020; Vrontis, Christofi, Tarba, Makrides, & Trichina, 2021). Using the SLR methodology we: 1) generate copious amounts of literature to analyze; 2) seek to answer specific research questions; 3) seek to extract relevant pieces of academic literature relating systematically to AI, HRM, and tactical HRIS.

3.1. Review Process

Following Collins et al. (2020) and Okoli (2015), we conduct this review in 2 phases: The first phase of this process filters literature, while the second phase extensively focuses on the content of each article. The goal of this SLR is to understand the representation of T-HRIS in published literature and how the representation of specific components differs. RQ1 seeks to gain a complete understanding of which components of T-HRIS exist in published literature. RQ2 seeks to understand how the components of T-HRIS have been represented in literature by identifying the analysis of the paper (empirical analysis, qualitative analysis, conceptual analysis, or literature review). Through this SLR, we seek to provide the research community with a review that investigates AI within HRM and T-HRIS. Considering AI and HRM are multidisciplinary (Vrontis et al., 2021), we decided to utilize the following databases:

1) Business Source Complete (EBSCO) (Nolan and Garavan, 2016; Vrontis et al., 2021)
2) AIS eLibrary (AIS) (Collins et al., 2021;)
3) Web of Science (WOS) (Collins, Dennehy, Conboy, & Mikalef, 2021; Di Vaio, Palladino, Hassan, & Escobar, 2020; Pisani, 2009)
4) ABI-INFORM (ABI) (Baskerville & Myers, 2009; Nolan & Garavan, 2016).

Upon identifying our databases, we established our inclusion and exclusion criteria for Phase 1 (Journal Demographic Filtration) and Phase 2 (Content Filtration). For Phase 1, there are two filtration steps: 1) the initial search and 2) the journal verification. Our inclusion and exclusion criteria consisted of 9 factors (5 for inclusion, 4 for exclusion).

We identified the following as necessary components to include a piece of literature for the initial search (step 1, Phase 1). The article must be: 1) peer-reviewed; 2) written in English; 3) published between 2014-2020; 4) an academic article or conference proceeding (Collins et al., 2021; Dhamija and Bag, 2020; Di Vaio et al., 2020; Nolan and Garavan, 2016; Qamar et al., 2021; Scandura and Williams, 2000). The exclusion of literature occurred if it: 1) was not written in English, 2) was not peer-reviewed or was non-academic, 3) was an editorial or simulation piece.

For the journal verification (step 2, Phase 1), we identified 90 academic journals (Appendix A from a wide range of disciplines that have historically published academic articles and conference proceedings relating to HRM and AI (Collins, Dennehy, Conboy, & Mikalef, 2021; Di Vaio, Palladino, Hassan, & Escobar, 2020; Pisani, 2009; Qamar, Agrawal, Samad, & Chiappetta Jabbour, 2021; Vrontis, Christofi, Tarba, Makrides, & Trichina, 2021). These publication sources serve as inclusion criteria #5 and exclusion criteria #4. We included the article if it belonged to the 90 journals or excluded it if it did not belong to any of those journals.

Once the journal verification state is complete, Phase 2 of the methodology beings: The Content Filtration phase. The inclusion and exclusion criteria of this phase consist of two steps. The first step is a title, abstract, and keywords (if provided) review, where we reviewed the title, abstract and associated keywords of the article to see if it matched our pre-established definitions of T-HRIS (Table 1 and Table 2) and AI Methods (Table 4). We also deleted duplicate articles within step 1 of Phase 2. The second step of Phase 2 consists of reviewing the article in its entirety to verify it met the requirement to be an article whose focus is on AI and T-HRIS components of HRM.

Once the inclusion and exclusions criteria became concrete for Phase 1 and Phase 2, we then sought to standardize our search string. One general search string strategy is to base the string on specified research questions and a list of synonyms (Collins et al., 2021; Kitchenham, 2012). We pulled from our research questions and pre-defined AI methods (see Table 4). Our search string consists of two pieces. The first piece is our key phrases regarding AI, while our second piece comprised keywords relating to HRM, HRIS, and HRMS. We used a Boolean practice when developing our search string. The "OR" operator exists between different words. The "AND" operator's purpose is to connect keywords. The use of parentheses compartmentalized the AI-specific keywords from the HR-specific terms. Table 5 outlines the search string used on all databases chosen.

3.2. Methodology in Action

Figure 2 demonstrates the selection process of our literature. Plugging the standardized string into each database, cumulatively yielded 315,053 articles. Isolating the articles which met the date, language, and peer-review requirements, achieved a total of 36,856 articles. Subsequently we filtered based on the inclusion and exclusion criteria previously discussed. Following this step, we further sorted through these articles based on the academic journals to which they belonged, yielding a tertiary selection of 697 articles from the four publication sources (EBSCO: 29; AIS: 246; WOS: 79; ABI: 343).

The tertiary selections from Phase 1 feed Phase 2 of our methodology. From this number (697), we look at the content of each article selected. For step 1 of phase 2, we reviewed each article's title, abstract, and keywords based on definitions established in section 2 (Table 1, Table 2, and Table 4). Phase 2 was our initial screening to validate which of the 697 articles truly connected AI with T-HRIS within HRM. We also took this time to delete duplicate articles from the databases to secure a list of unique articles. Upon completing step 1 of Phase 2, we yielded a secondary selection of 74 unique articles. These 74 articles fed the last and final step of our method, which required us to read through the entirety of each article and validate that they were genuinely related to AI practices within T-HRIS components of HRM. Of these 74 articles, 33 met the criteria to be the primary studies selected based on our SLR.

4. FINDINGS

The findings and analysis of literature within AI and HRIS are presented in this section.

4.1. Managerial T-HRIS Research

Managerial T-HRIS provides an avenue to focus on the more human-centric responsibilities HR professionals are responsible for managing and nurturing. Figure 3 showcases three unique branches which fall within this managerial T-HRIS literature umbrella. The first branch of this consideration is employee performance and satisfaction, and the second is discipline management systems. Understanding employee performance, satisfaction, and discipline within an organization are imperative to securing retention and potentially understanding where weaknesses exist. Given that the nature of delivering feedback is sensitive explore AI-applications to streamline these managerial responsibilities provides HR professionals with more time to understand and interpret the analysis provided by the machine and carefully deliver the feedback and findings to the employee in question. Furthermore, the exploration of AI within compensation and benefits systems provides HR professionals with a tool to ensure their employees are engaged and receiving fair and correct entitlements based on their unique circumstances (Hughes et al., 2019).

Table 5
AI and HRM Key Word Searches

Topic	String
Artificial Intelligence	("AI" OR "artificial intelligence" OR "Natural Language Processing" OR "NLP" OR "Chatbot" OR "Machine Vision" OR "Machine Learning" OR "ML" OR "Recommendation Engine" OR "Deep Learning" OR "Neural Networks")
Human Resource Management	("Human Resource Management" OR "HRM" OR "Human Resource Information Systems" OR "HRIS" OR "Human Resources" OR "HR" OR "Human Resource Management Systems" OR "HRMS")
	Full String
	("AI" OR "artificial intelligence" OR "Natural Language Processing" OR "NLP" OR "Chatbot" OR "Machine Vision" OR "Machine Learning" OR "ML" OR "Recommendation Engine" OR "Deep Learning" OR "Neural Networks") AND ("Human Resource Management" OR "HRM" OR "Human Resource Information Systems" OR "HRIS" OR "Human Resources" OR "HR" OR "Human Resource Management Systems" OR "HRMS")

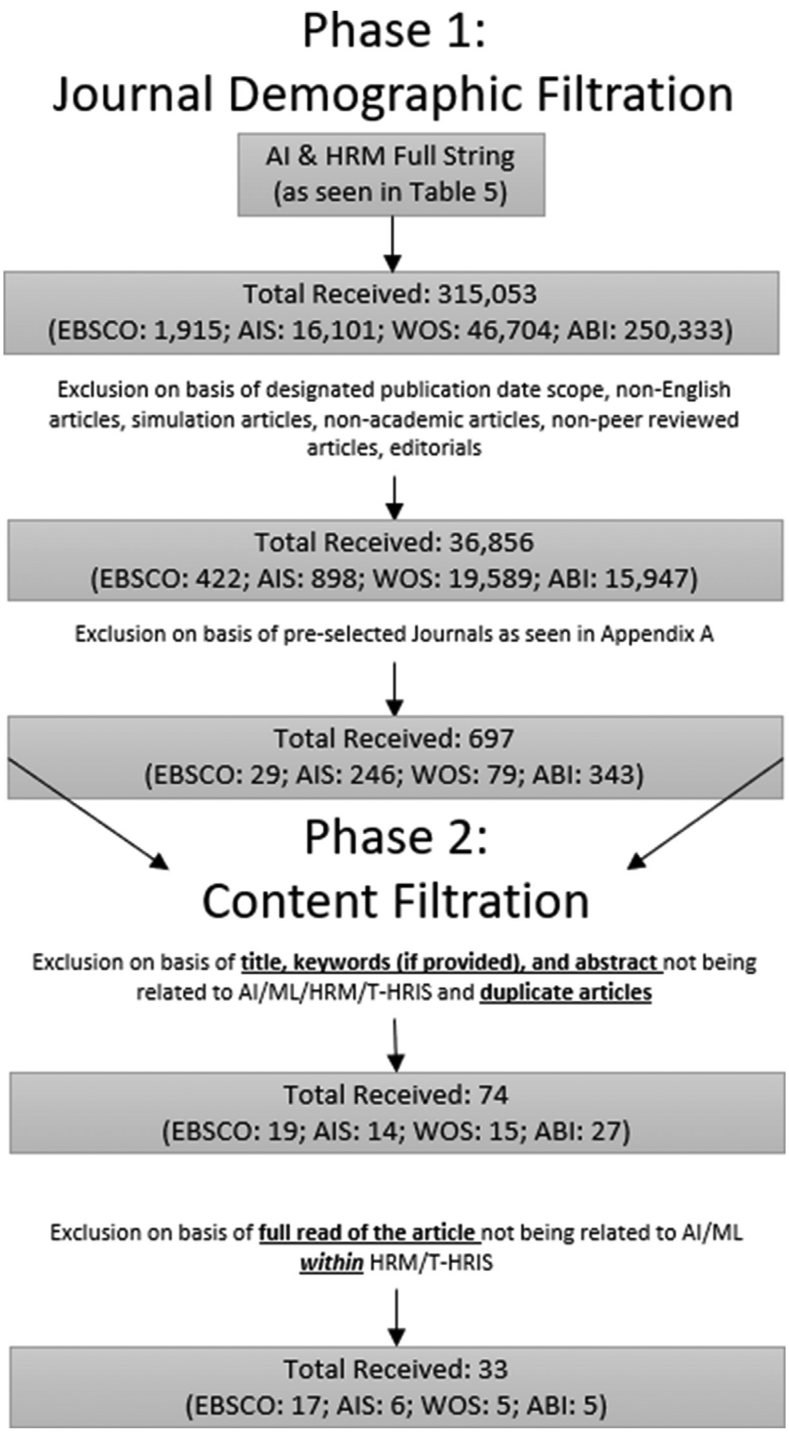


Fig. 2. SLR Methodology

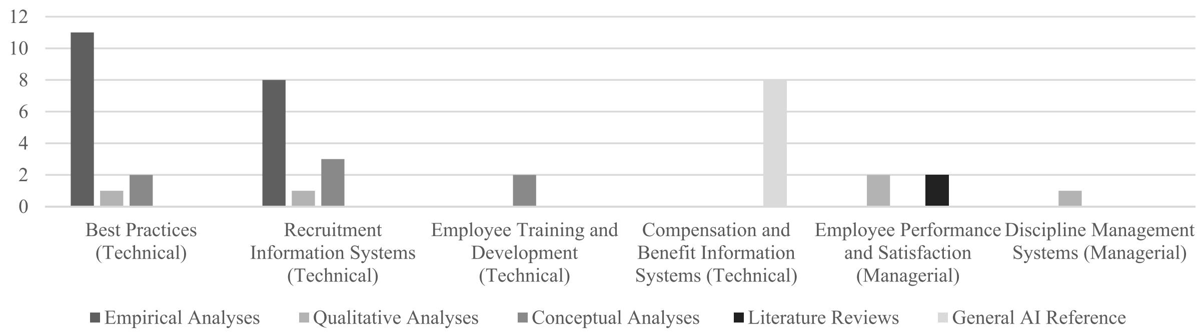


Fig. 3. Analysis Representation

4.1.1. AI Literature within Employee Performance and Satisfaction

Pratt et al. (2021) investigate how technological-based communication tools can autonomously engage with employees and streamline processes via simulating human-to-human interactions. Their proposed model provides insight into an employee's satisfaction and performance concerning cultural and motivational factors, communication techniques, and the work descriptions of each employee. The presented model demonstrates essential factors to consider in AI-based communication tools and how they interact with one another. Where face-to-face techniques excelled indirectly in motivating employees and increasing their satisfaction, the AI-enhanced communication tool experienced more of a challenge when motivating and directly influencing an employee's satisfaction. Thus, the tactical act of communicating with employees and making that connection presented a challenge for AI-enhanced communication tools within (Pratt et al., 2021) research.

Similarly, (Tong et al., 2021) research explores AI's theoretical application in employee performance feedback. It empirically evaluates the quality of feedback (which may increase employee productivity) and the employee perception of the AI from a field experiment. Given AI's superior standardized and analytic nature, evaluating employee input and output, providing areas of improvement, and predicting future performance has become a streamlined process for HR professionals and T-HRIS applications. HR teams would manually review and scrub an employee's record and identify positive/negative trends. An AI-enhanced T-HRIS application can do the analytics for them and provide recommendations directly to the employee. Despite the brutally honest system, AI feedback can negatively affect the employees by disclosing their weaknesses.

Consequently, direct honesty discourages them from furthering (otherwise known as the "adverse disclosure effect"). This effect creates a unique paradox when considering improving an employee's motivation, satisfaction, and performance: Do not communicate the weaknesses directly and allow them to achieve complacency or disclose the employee's areas of improvement, potentially discouraging them further to seek improvement and achieve the same complacency. Ultimately, (Tong et al., 2021) experiment and research conclude that these considerations coexist, and the mitigation of adverse disclosure effects is dependent on an employee's tenure within a firm.

Both (Pratt et al., 2021) and (Tong et al., 2021) highlight one of the most significant weaknesses AI has within the managerial T-HRIS applications, lacking emotional intelligence. Within employee performance and satisfaction, an element of emotional intelligence requires effective and meaningful communication with employees. Managers and HR professionals need to have the emotional wherewithal to cope with difficult emotional hurdles that may present themselves. However, they also need to have the ability to communicate effectively while respecting their employees' boundaries. Prentice et al. (2020) explore this notion by empirically studying the effects emotional intelligence and AI has on employee retention, satisfaction, and performance within the hotel industry. The findings within their study conclude that emotional intelligence is a valid predictor of employee attitudes and behaviors, and that AI does well to focus on the technical and functional efficiency an employee has on organizational performance. Despite having a significant impact on employee performance, AI holds little significance about employee retention, further expanding upon the importance of establishing interpersonal connections with employees.

Finally, (Garg et al., 2021) provide insight to employee satisfaction within the logistics and freight forwarding organizations by developing a novel approach to analyzing employee feedback and satisfaction using AI algorithms. This further empowers an employee to answer a climate survey on their experiences, analyzes the respondent's input, and provides the organization actionable insight which allows organization stakeholders more insight to how to improve employee engagement, retention, and efficiency. Through this analysis, (Garg et al., 2021) provide both the professional and academic community insight on how the use of AI has a profound effect on the organization and its respective employees. These capabilities benefit the employee's voice and provides an avenue to communicate concerns and boons directly to the organization.

4.1.1.1. AI Literature from SLR regarding Employee Performance and Satisfaction. The SLR we undertook yielded 4 total articles which featured Employee Performance and Satisfaction. These 4 articles were consistent of 2 qualitative paper and 2 literature reviews. The qualitative analyses conducted gives insight to individualization of HRM practices and AI-mediated social exchanges and how AI impacts HRM practices and the attitudes and behaviors of employees. Their collective findings via interviews suggest generational differences in the adoption of AI and that AI-enabled bots and digital personal assistants are utilized in analytical and routine tasks involving employees (Kaminska and Borzillo, 2018; Malik et al., 2020). Within Malik et al.'s (2020) analysis, is suggested that these AI-enabled programs bolster HR cost-effectiveness and enhance the overall employee experiences, thereby increasing employee commitment and satisfaction within an organization. While, Kaminska and Borzillo (2018) suggest fundamental differences between Genration X and Y employees and the adoption of enterprise social networking systems driven by AI. The 2 literature reviews discovered within this SLR provide insight to how AI technologies have infiltrated organizational settings by influencing personnel development. Specifically, Kotera et al. (2019) provide a meta-analysis on natural language processing AI technologies and how it affects the feelings and thinking of employees within the work environment. While Kock et al. (2020) systematically review AI capabilities within employee performance reviews and how cognitive factors relating to rating quality and personality-related factors differ within HRM practices.

4.1.2. AI Literature within Discipline Management Systems

The research conducted by Dressel and Farid (2018) explores a new light of discipline management by evaluating the predictive analysis of recidivism within the criminal justice system. With the exponential growth of data and the development of AI-empowered machines to cope with this growth, commercial software runs the risk of developing inaccurate predictions that could affect human beings' lives. Specifically, AI-algorithmic developments have fueled tools like the Correctional Offender Management Profiling for Alternative Sanctions (COMPAS), which predicts a defendant's risk of committing a misdemeanor or felony within two years of assessment from 137 different features about the individual and their respective criminal history. (Escalante et al., 2017)'s analysis compared the overall accuracy and bias in human assessments (individuals with no criminal justice background) with the algorithmic assessment of COMPAS. Through (Dressel and Farid, 2018) 's empirical analysis, the prediction of the COMPAS algorithm was no more accurate or fair than the predictions of humans with little to no criminal justice experience. The results were near indistinguishable, thus showcasing the dangers of blindly implementing AI practices in high-risk decisions where human lives are on the line.

Formal grievance processes have also experienced an AI facelift, providing employees with a discrete avenue to communicate and report abhorrent behaviors within an organization, minimizing the fear of retribution and feelings of shame. Olson (2018) highlights Spot's online chatbot, which engages with the harassment victim on their experiences. This chatbot utilizes NLP techniques to provide a "cognitive" interview to the employee and gain insight discretely on details about their harassment claim. As Spot has grown within the company, it has developed analytic capabilities to gauge organizational diagnostics regarding the health of the organization's corporate cultures. This development has provided insight into where reports are deriving from and identifying patterns that HR professionals cannot humanly conceive through pattern recognition. Although it may not solve the problems directly, (Escalante et al., 2017) concludes Spot gives insight into more significant issues that employees are not willing to speak about aloud.

4.1.2.1. AI Literature from SLR regarding Discipline Management Systems. The qualitative analysis conducted by Bhattacharyya and Nair (2019) discusses how future of work applications (robotics, artificial intelligence, internet of things) have multiple facets via semi-structured open-ended interviews with 26 respondents. Their analysis gives insight to how organizations will have data dependencies and that employee will be expected to synthesize data for sense making and decision processes which could affect work performance and disciplinary actions (Bhattacharyya and Nair, 2019).

4.2. Technical T-HRIS Research

AI applications within Technical T-HRIS have enabled once time-consuming and task-saturated processes to be automated and streamlined for both the employee and customer. These tasks are data-driven to ensure the organization is optimized and can maintain or obtain a competitive edge. The first branch of Technical T-HRIS we will review concerning AI is the "Best Practices" branch. Four prominent pieces of literature explore how AI has influenced workflow and customer engagement within the Best Practices branch of T-HRIS. The second branch explored will be the Recruitment Information Systems component which contains four separate pieces of literature which review the effects and consequences of implementing AI within these processes. The third branch is the Employee and Training Development Systems branch. This branch contains three pieces of literature that explore the effects of AI within employee education systems. Compensation and Benefits Analysis is the last branch, which focuses primarily on securing employee benefits and financial considerations relative to organization resources and employee qualifications. The exploration AI within compensation and benefits systems provides HR professionals with a tool to ensure their employees receive the correct entitlements based on their unique circumstances while effectively budgeting company expenses.

4.2.1. AI Literature within Organizational Best Practices

Cain et al. (2019) provide a compilation and systematic review of current studies and journals which examine the impact of AI and robotics have within the hospitality and tourism industry. Their review proposes emphasizing the importance of exploring research within the human-robot interaction as these technologies grow to help streamline processes to give time back to employees. Furthermore, they insist that research should focus on understanding how customers interact with automated AIs capable of performing an employee's tasks quickly.

(Rahmani and Kamberaj, 2021) review how introducing AI-enhanced chatbots that interact with customers and employees provides organizations with machines capable of learning and automatically adapting to the environment based on data received and processed. Their analysis provided insight into how the automation of administrative tasks within employee onboarding, process improvement, and recruitment provide humans with the necessary information, time, and psychological energy to make well-informed decisions for their organization. Their paper assesses how an organization can use chatbots to streamline administration and explores what technology they can run. It discusses how AI-enhanced chatbots can simulate comparably "human" conversations using NLP and machine learning processes to enhance the customer experience.

Further expanding on the use of Chatbots, (Majumder and Mondal, 2021) provides an in-depth overview of the use of chatbots within HRM and the streamlined processes. The influence chatbots have within decision-making processes is prevalent, but they also facilitate a better understanding of AI and ML innovations among the employees within an organization. As an example, (Majumder and Mondal, 2021) highlight the innovative application of an AI chatbot within employee training modules, making them more interactive and engaging directly with the employee, compared to the mandatory videos these same employees once had to watch.

Lastly, Chakraborty and Kar (2021) provide an example on how AI can be used to mine data to gain insight on the wellbeing of employees during the unprecedented times following the COVID-19 pandemic. Specifically, they conducted a mixed methodology analysis which utilized AI technologies to mine from Twitter in addition to conducting interviews to identify challenges COVID-19 created for employees across the work spectrum. Specifically, they addressed how professionals across industries are affected by the pandemic, how that impact translates into academia, and the nature of the impact on the social welfare of faculty members. Ultimately, their analysis concluded there are systemic challenges revolving around infrastructure and digital readiness, workforce demand and supply, and job losses.

These innovations spotlight the benefits of having a machine engage directly with the employee to answer questions they may have regarding pay, benefits, or any other HR-related topic. Not only does this free up time for the HR professional, but it also provides a near-human experience for the employee to directly engage with an HR entity to get the information they were looking for more quickly.

4.2.1.1. AI Literature from SLR regarding Organizational Best Practices. Through our SLR, organizational best practices saw an influx of research within AI capabilities as it was the most represented T-HRIS component with 11 empirical articles, 2 conceptual research articles, and 1 qualitative research article. Regarding the empirical analyses, predictive AI methodologies to enhance organization performance resonated greatly in organizational best practices (Bani-Hani and Khasawneh, 2019; Chang and Jung., 2017; Cheng-Kui et al., 2020; Fehrenbacher, 2017; Jabr and Zheng, 2014; Saha et al., 2016). Furthermore, these empirical analyses provide insight to how AI technologies can replicate and influence HR decision-processes within organizations, highlighting both the challenges and benefits that come with the responsibility of leveraging these autonomous systems (Bani-Hani and Khasawneh, 2019; Castillo et al., 2018; Chang and Jung., 2017; Cheng-Kui et al., 2020;

Fehrenbacher, 2017; Jabr and Zheng, 2014; Kretzer and Maedche, 2018; Lankton et al., 2015; Lee and Ahn, 2020; Rybinski and Tsay, 2018).

The conceptual research articles identified within this SLR regarding best practices provide insight to how to cope and navigate computing systems which take on human-like abilities to make decisions within its environment while providing transparency and a sense of intuitive intelligence (Huang and Rust, 2018; Scheutz and Venkastesh, 2020). These conceptual articles provide insight to how an organization and its employees can better interface with AI technologies to enhance workplace procedures, services, and interactions (Huang and Rust, 2018; Scheutz and Venkastesh, 2020).

Finally, one qualitative research article regarding best practices was identified within our SLR. Yorks et al. (2020) interview 7 doctors and nurses from a variety of medical fields to gain insight to AI adoption within the workplace and how it has transformed processes. Their interview findings provided insight to how certain professional demographics (healthcare workers) are reacting to the technological evolution within their respective workplaces.

4.2.2. AI Literature within Recruitment Information Systems

Johnson et al. (2020) explore implementing electronic HRM and AI to help recruit highly qualified employees, increase individual retention rates, and decrease the amount of time it takes to onboard/replace new employees within the hospitality and tourism industry. Their research proposes that AI facilitates two cognitive elements that promote decision-making within an organization.

The first introduced is a cognitive insight which implies the algorithms and ML techniques AI utilizes assists in interpreting the copious amount of data received and discovers patterns not previously identified by the organization. Such advancements have enabled organizations to engage in activities more effectively like predicting potential candidates for hiring and potential internal hires within the organization. The second cognitive element Noone and Coulter (2012) address is cognitive engagement, which implies using a chatbot to simulate a human-like and near-natural social interaction with the employee and customer through NLP technologies. These intelligent agents help with customer decisions and employee questions within the “tech-support” realm giving time back to HR professionals at the tactical level (Noone and Coulter, 2012).

Given the recent global pandemic, Koch et al. (2021) utilize advanced web mining robotics to evaluate how companies in Germany adjusted to the new processes caused by COVID-19. Given the increased emphasis on public safety, HR professionals heavily relied on technological capabilities to continue the necessary hiring and recruitment processes. Specifically, these authors explored how the German public sector job market reacted to the pandemic and how this pandemic affected IT professionals with regards to electronic recruitment systems (job listings, interview processes, telework capabilities). By utilizing intelligent robots to scrape data necessary for their research, Koch et al. (2021) were capable of conjuring results which indicate the importance of advertising work from home availability, increased planning uncertainty (longer job postings), and that job advertisements with a healthcare background grew less strongly than they expected.

To expand on the utilization of intelligent agents and chatbots, Rahmani and Kamberaj (2021) further develop the research by assessing how a company can effectively use chatbots, the technology on which chatbots run, and evaluating how well a chatbot can simulate a conversation as human as possible. Their academic exploration showcases a variety of different types of chatbots and their respective architectures. This in-depth exploration provides HRM professionals with insight into what chatbots exist. However, it also provides insight into how they could be utilized in a professional environment to alleviate administrative burden. Upon interviewing a director from an IT company and an online survey of 210 respondents, (Stewart, 2007) could determine the following: 1) The implementation of AI in automated tasks has proven to be beneficial for employees and customers. 2) AI should not be responsible for the entire procedure of hiring new employees. 3) Empathy and emotional bias should play a role in the employee recruitment process, where AI can help with eliminating bias the human-factor is still important.

4.2.2.1. AI Literature from SLR regarding Recruitment Information Systems.

Within the SLR we conducted, 8 empirical, 3 conceptual, and 1 qualitative articles were discovered regarding Recruitment Information Systems. Specifically, the empirical articles provided thorough analyses on how data-mining techniques on unemployment rates can influence recruitment systems (Li et al., 2014) and how well AI systems can enhance the candidate selection process within company recruitment initiatives (Karatop et al., 2015; Martinez-Gil et al., 2020; Pessach et al., 2020; Sajjadiani et al., 2019; van Esch et al., 2019). The 3 conceptual papers expanded on how AI can impact how a company brands and markets itself to potential recruits (Dabirian et al., 2017). Additionally, these conceptual papers provide insight to when recruiters should incorporate AI within practices (Black and van Esch, 2020) and how to use it to develop models which can predict company turnover via case-based reasoning (Wang et al., 2017). Finally, the qualitative research article discovered within this SLR regarding Recruitment Information Systems provides insight to how customizable, technology-based services connect organizational learning and recruitment via interviewing 12 soft-ware firms located within Norway. These interviews highlighted a tension associated with the need to create stable individual knowledge systems for employees and dependencies on external software capabilities to accumulate knowledge (Jøranli, 2018).

4.2.3. AI Literature within Employee Training and Development Systems

Maintaining an employee’s professional development and growth within an organization is crucial in securing various organizational goals. For one, ensuring employee participation in annual security compliance and company-specific module training is a responsibility that are levied upon HR personnel and departments writ large. Mandatory training compliance aside, grooming employees by presenting educational opportunities eligible for postures for internal hires and retention benefits. Understanding that the number of employees within an organization varies, T-HRIS processes are ripe opportunities for AI to grow and streamline educational processes. For example, a machine’s ability to recommend specific training to an employee based on an analysis of their aptitude, interests, and success potential is neigh. These capabilities empower HR professionals to explore an employee’s potential further and not be burdened with the hours of analysis it would take to run this analysis on each employee.

To further expand, Noone and Coulter (2012) evaluate Zaxby’s, a popular fast-food restaurant originating from Athens, GA, and how they utilize autonomous robotic applications to reduce service times and food waste substantially. They further explore how these same AI applications can increase labor training efficiencies and opportunities for enhanced process management and decision-making through demand prediction and production management AI applications. Where information had been passed manually from person to person, quick service restaurants, like Zaxby’s, have successfully applied AI-enhanced tools which store production knowledge to enhance continuity of best practices to train future employees upon arrival.

Maettig and Foot (2020) further explore improving technical T-HRIS concerning employee training by reviewing industrial applications using intelligent augmentation and human-in-the-loop strategies. Like Rahmani and Kamberaj, 2021, Maettig and Foot (2020) acknowledge that digital training assistants are great for storing best practices from older employees to train newer hires. They further acknowledge the value in having digital assistants analyze performance trends; however, they address that AI-enhanced digital assistants lack the detailed experience knowledge that older employees may have. Particularly, the implicit knowledge of experienced employees cannot be easily replicated on digital platforms.

Similarly, Xu and Xiao (2020) introduce the concept of using AI-enhanced virtual reality simulators to enhance mandatory employee training, increasing employee participation by 79%. Through their empirical analysis, these authors highlighted the application of virtual reality technology within enterprise HRM, which can improve efficiency, reduce costs, and enhance the competitiveness of organizations across their respective industries.

Thus, these AI-enhanced training assistants are best used as augmentation devices to streamline the development of employees. Methods of improvement include tracking, recommending, and analyzing training, allowing humans to play a prominent role in filling in the gaps, and adding a tailored and personalized approach to the onboarding process.

4.2.3.1. AI Literature from SLR regarding regarding Employee Training and Development Systems. Regarding Employee Training and Development Systems, our SLR provided two articles which expanded upon the incorporation of AI. The first article is empirical and conceptual in nature. Through interviews, Maity (2019) discovered 33.33% of respondents believed intuitive e-learning interfaces would be beneficial within their workplace. Maity (2019) further concludes that 92.6% of HR training professionals believe that AI software within the digital learning environment should interact with employees to further their engagement and development within the company. The second article is conceptual in nature, as Lima (2020) explores the smart organizations and how companies can start to build smarter learning platforms to increase performance levels and help innovative organizations develop talented, creative, and diverse employees.

4.2.4. AI Literature within Employee Compensation and Benefits Systems

The advancements of AI within resource-driven T-HRIS are also within the scope of employee compensation and benefits. In particular, Robert et al. (2020) explore how organizations have rapidly deployed AI systems to manage their employees and provide three solutions to address AI unfairness within decision-making processes. Establishing the operationalization of an organization's management practices is crucial before delegating specific tasks to AI technologies. Regarding compensation and benefits, this pushes organizations to move beyond vague statements of what is considered fair to more specified metrics to secure equal practices and train the AI. Should an AI be used to determine an employee's compensation or benefits package, the organization should determine whether employees work similar hours in the same position and receive equal pay regardless of specific demographics relating to the employee (sex, age, race).

Ahmed (2018) furthers this discussion by highlighting specific HR functions which AI can permeate and streamline. Data analytics relating to pay equity is crucial in securing fair and ethical compensation and benefits practices within an HR department. Not only does an HR department need to balance the needs of the organization's employees, but it also must secure budgeting expenses appropriately. Allowing an AI to undertake the burden of tediously number-crunching and inferring the unfathomable amount of information collected on its employees enables HR professionals with the time to review the analysis and validate fair practices. (Ahmed, 2018) provides insight into how crucial interpretability and transparency of the AI mechanism is, as it provides HR professionals with an insight into the justification the AI produces (Bourhis et al., 2019). Thus, this provides HR departments a more trustworthy process (Hmoud and Várallyai, 2020). The notion of using black-boxes within high-stakes decision-making, especially within HR departments, is unquestionably discouraged, as the use of "black-box" modeling techniques allows for potential unforeseen biases to develop, resulting potentially in unethical practices within an organization (Ahmed, 2018; Amer-Yahia et al., 2020; Rudin, 2019).

4.2.4.1. AI Literature from SLR regarding Employee Compensation and Benefits Systems. Within this SLR, there were no articles regarding Employee Compensation and Benefits Systems discovered within the 33 articles that met our selection criteria.

4.3. How have the components of AI and T-HRIS been represented in the literature?

This research aimed to identify how the components of T-HRIS are represented within the literature. Upon reviewing the methodologies of these articles, we identified that 19 were empirical analysis, 5 were qualitative analysis, 7 were conceptual analysis, and 2 were literature reviews. Based on this SLR, empirical studies dominated the results of our SLR, as our technical T-HRIS components dominated the total count number of articles.

Through our extensive review and using the definitions outlined in Table 2, we identified which AI methodologies and applications are more represented within HRM and T-HRIS literature (Table 6). Regarding the AI-type (y-axis), the variable titled "General AI Reference" represents an article that referenced AI in a general sense and did not specify an AI method within their paper. Using the definitions our analysis concluded a high representation of machine learning techniques and general AI reference. We further identified a substantially lower representation of machine vision methodologies within T-HRIS and HRM applications.

4.3.1. Component Representation within each Analysis-Type

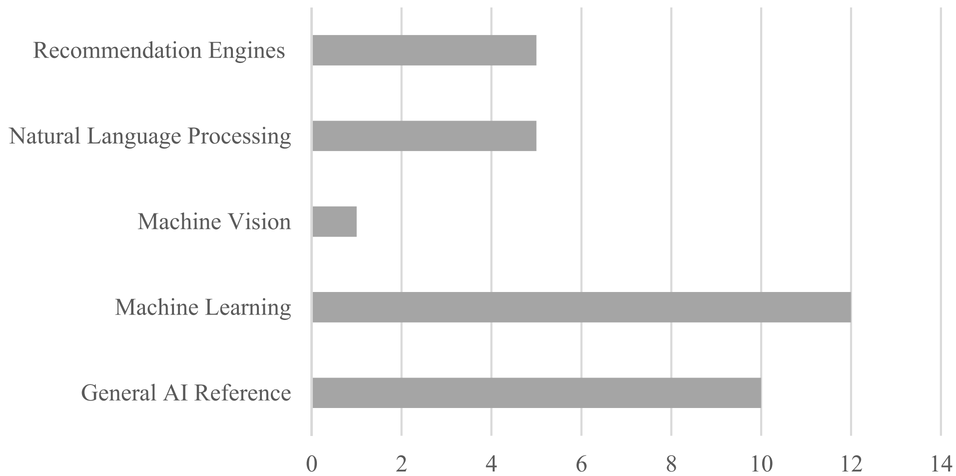
Of the 19 empirical analyses, 5 qualitative analyses, 7 conceptual analyses, and 2 literature reviews identified, Best Practices and Recruitment Information Systems and Employee Training and Development were the most represented component of T-HRIS regarding AI application research. The managerial components, Employee Performance and Satisfaction and Discipline Management, did not have representation with regards to empirical analysis. Furthermore, Compensation and Benefit Information Systems component of technical T-HRIS was only referenced passively and in general terms of AI applications in 8 articles within this SLR; there were no articles identified within this SLR which primarily focused on Compensation and Benefit Information Systems and AI applications (see Figure 3). Given that technical T-HRIS components are resource-driven and based on policies and SOPs, we have identified through our SLR that empirical studies are currently more represented by technical T-HRIS components rather than managerial T-HRIS.

Specifically, the Policies and Standards of Practice components of technical T-HRIS are most represented by empirical research. Within the empirical analyses from our SLR, we further identified common AI themes which these articles highlighted (see Figure 4). This provides insight to the lack of empirical studies and analyses within managerial T-HRIS components. For the components which were represented (Best Practices, Recruitment Information Systems, and Employee Training and Development), our SLR identified the underrepresentation of machine vision applications within HRM and T-HRIS, while the other methodologies (Recommendation Engines, Natural Language Processing, Machine Learning, and AI Writ Large) are better represented within research.

Given the context of this SLR, we have identified a potential avenue to expand upon empirical academic research within T-HRIS. Within our rigorous SLR, no managerial T-HRIS components were represented within the group of empirical articles, giving reason to believe future research could be done in this field to expand the T-HRIS research agenda.

Of the four qualitative studies, our SLR identified, four T-HRIS components were represented (Best Practices, Recruitment Information Systems, Employee Performance and Satisfaction, and Discipline Management Systems). Each component contained one piece of literature which focused on an A1 methodology. Comparatively, the qualitative analysis article is the second least represented article type within this SLR. Nevertheless, it was the only article type to contain equal representation for managerial and technical T-HRIS.

Table 6
AI Representation within SLR



Appendix A
Academic Journals

Information Systems and Management (18):	*General Management Journals (40)*:
Decision Support Systems	Academy of Management Annals
European Journal of Information Systems	Academy of Management Journal
Expert Systems with Applications	Academy of Management Review
Government Information Quarterly	Administrative Science Quarterly
Information and Management	Asia Pacific Journal of Management
Information and Organization	Business Horizons
Information Society	Business Strategy and the Environment
Information Systems Frontiers	Decision Sciences
Information Systems Journal	European Journal of Operational Research
Information Systems Research	Global Strategy Journal
Information Technology and People	Human Relations
International Journal of Electronic Commerce	Industrial Relations
International Journal of Information Management	International Business Review
Journal of Association of Information Systems	International Journal of Management Reviews
Journal of Information Technology	International Marketing Review
Journal of Management Information Systems	Journal of Applied Behavioral Science
Journal of Strategic Information Systems	Journal of Applied Psychology
Management Information Systems (MIS) Quarterly	Journal of Business Research
Human Resource Management Journals (9):	Journal of International Business Studies
Human Resource Management	Journal of International Management
Asia Pacific Journal of Human Resources	Journal of International Marketing
Employee Relations	Journal of Knowledge Management
Human Resource Management Journal	Journal of Management
Human Resource Management Review	Journal of Management Education
International Journal of Human Resource Management	Journal of Management Studies
International Journal of Manpower	Journal of Occupational and Organizational Psychology
New Technology, Work and Employment	Journal of Organizational Behavior
Personnel Review	Journal of Service Research
Human Resource Development Journals (12):	Journal of Vocational Behavior
Advances in Developing Human Resources	Journal of World Business
Career Development International	Management International Review
Education and Training	Management Science
European Journal of Training and Development	Organization Science
Human Resource Development International	Organization Studies
Human Resource Development Quarterly	Organizational Behavior and Human Decision Processes
International Journal of Training and Development	Personnel Psychology
Journal of Education and Work	Psychological Bulletin
Journal of Management Development	Strategic Change
Journal of Vocational Education and Training	Strategic Management Journal
Journal of Workplace Learning	Work, Employment and Society
Human Resource Development Journals Continued (12):	*Small Business Journal (7)*:
Learning Organization	Entrepreneurship Theory and Practice
Computer Science and Engineering Journals (4):	International Entrepreneurship and Management Journal
Computers and Industrial Engineering	International Journal of Entrepreneurial Behavior and Research
Computers in Human Behavior	International Journal of Entrepreneurship and Innovation
International Journal of Human-Computer Studies	International Small Business Journal
Journal of Computer Mediated Communication	Journal of Small Business and Enterprise Development
	Journal of Small Business Management

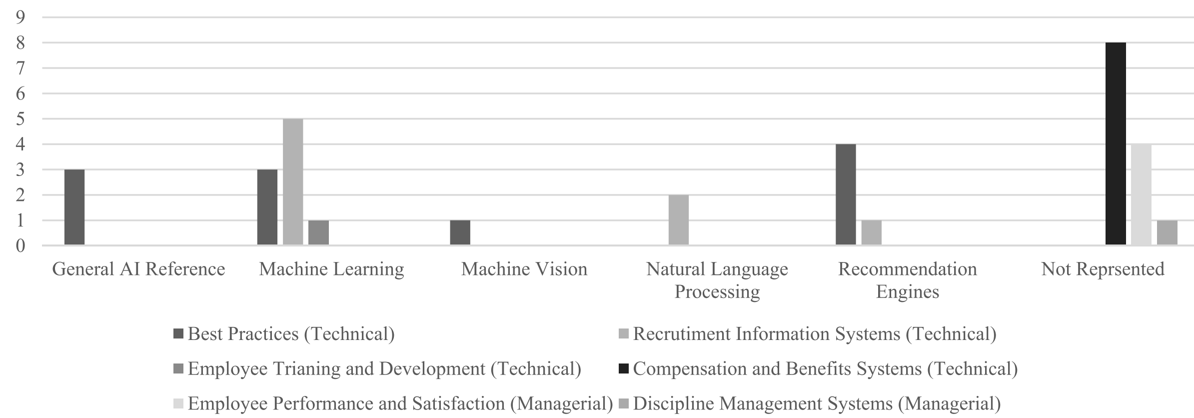


Fig. 4. Empirical Analysis Break Down

Of the seven conceptual analyses, our SLR identified, there was representation in both technical T-HRIS and managerial T-HRIS components. Like the empirical representation, the conceptual analysis favors technical T-HRIS components considering six of the seven articles related to Best Practices (three articles), Recruitment Information Systems (two articles), and Employee Training and Development (one article). The only component of managerial T-HRIS represented was Employee Performance and Satisfaction, leaving room for future research opportunities.

Finally, of the two literature reviews, our SLR identified, only one component out of all six possible (four technical, two managerial) was applicable. The Employee Performance and Satisfaction component was represented in both reviews, leaving room for future literature reviews analyzing technical T-HRIS and AI applications.

5. DISCUSSION

Based on the results analysis of our research, the application of AI within tactical HRIS practices needs further exploration within academia in a variety of areas. First, we consider the contributions this SLR has provided to the existing literature and surrounding communities. Secondly, we discuss future research opportunities this SLR has shined a light upon to further develop this field and agenda. Lastly, we discuss the limitations of our research and how future scholars can mitigate the limitations we faced.

Through our research, we seek to shine a light on the importance of AI and HRM practices through the exploration of existing literature relating to tactical HRIS components. The prominent growth of digitalization within the work force and the evolution of AI within HRM has helped improve areas like employee experiences and performance (Garg et al., 2021). Thus, our contribution highlights the importance of understanding where AI is best represented in tactical HRIS components and where academics writ large are focusing their attention. We sought to provide inductive insights to the current state of AI within HRM based on a literature-driven and systematic methodology that is repeatable for future research opportunities to come for both the academic community and industry professionals.

With regards to research avenues to explore regarding AI applications within tactical HRIS components, we discovered several gaps which may help expand the agenda of AI within HRM. First, there is a glaring gap in published literature (relative to our search) between managerial and technical HRIS practices. Where task-oriented and data-driving HRIS components see more representation in literature, the more intuitive and emotionally intelligent practices lack attention. Comparatively, this provides an opportunity to dive into why this gap in research exists and further exploration as to why organizations veer away from incorporating AI into practices that require intuitive, genuine, human-centric perspectives.

Secondly, we showcase Employee Compensation and Benefits programs research lacks heavily in academic literature, given the parameters we set. Although we cast a large net of 90 journals to consider during our analysis, no articles of the 33 identified celebrated direct AI applications within Employee Compensation and Benefits programs. This discovery invites future scholars to empirically, qualitatively, and conceptually explore how AI applications directly affect benefits and compensation programs within an organization and make that tactical HRIS component the star of the article.

Moving forward, the implications of this research can equally guide the academic community and industry professionals on understanding where AI exists within T-HRIS. This offers an opportunity for synergy between the academics and industry professionals, as this work provides insight to potential research areas regarding T-HRIS components and where AI is lacking or is overrepresented. Furthermore, these findings provide an opportunity for industry professionals to educate themselves on potential technologies which may streamline monotonous processes. Moreover, the effects of this research provide the academic community with awareness to the state of which AI is explored and the lack of research within managerial T-HRIS components when compared to the technical spectrum.

6. CONCLUSION

The purpose of this research was to review the integration of AI within HRM and HRIS components; admittedly, there were limitations we encountered during our research that merit exploring. First, we used a broad range of keywords like “artificial intelligence” and “human resource management” within our search string to provide us a wide coverage of topics in HR and AI. This may have inhibited our ability to gather insights from other authors which may have emerged outside of the selected keywords used in our string. Furthermore, we limited our search to a specified number of research journals, which may have impacted the number we were able to generate and analyze within our search. Lastly, we were limited on the access to databases. To enhance this search, incorporating other reputable databases like SCOPUS may provide more robust results to incorporate in a researcher’s literature search.

Additionally, this paper presents an SLR analyzing AI-enhanced technical (data-driven) and managerial (human-centric) T-HRIS. The reviewed literature presents a research gap between technical and managerial T-HRIS, which is evident upon reviewing 33 articles across four different databases, six T-HRIS components, four different AI methodologies, and four article types. This analysis discovered that the more data-driven and task-orientated T-HRIS applications are saturated in literature, and the managerial practices are less represented. The review of existing research provides a foundation and direction for future research to address the gap between technical and managerial T-HRIS AI applications.

Going into this analysis, we set a goal to identify which T-HRIS components existed in academic literature and how they were represented and sought to answer the research questions derived from this goal. Based on our SLR, we could sift through 350,053 articles based on specified criteria and narrow the list down to 33 articles that met the requirements and parameters we sought to investigate. Upon completing our meticulous analysis, we have decided to address some opportunities for future research based on the SLR conducted: First, technical T-HRIS (resource and task-driven) components are overrepresented. There is potential for future exploration on the managerial T-HRIS components, which are more human-centric. Second, there are significantly more empirical studies when analyzing the relationship between AI and T-HRIS, leaving room to expand the research agenda by providing more qualitative analysis, conceptual analysis, and literature review research. In addition, out of all the literature analyzed within this SLR, to include Phase 1 and Phase 2 of our methodology, this research solely takes technical and managerial HRM and HRIS practices into consideration and individually analyzes them. This review also paves the way for future exploration regarding technical and managerial HRM and HRIS and its relationship with AI. Finally, based on our SLR, the Information Systems and Management publication community claims 15 of the 33 total articles, which gives us reason to believe these sources may be more receptive to research regarding AI and HRM practices. This highlights potential blind spots for other publication venues seeking analysis on AI and T-HRIS components.

Through this research, we seek to enhance research developments within the HR, IS, and AI communities by bringing to light gaps within existing literature through a systematic review. Although we faced limitations regarding our search string, journal analysis, and database usage, we reinforce the future research agenda by providing new avenues to explore. We further reinforce the motion that there is room for future academics and professionals to explore AI applications in managerial HRIS components. Similarly, we showcase the research opportunity for Employee Compensation and Benefits systems research and AI applications. To conclude, we celebrate the academic and literature advancements of AI within HRIS and HRM and are excited highlight the research potential which exists within tactical HRIS components. This review provides the necessary groundwork to further grow this research agenda and gain a deeper understanding of why the identified gaps exist within literature and where professional and academic stakeholders can focus their attention to further grow the field.

Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

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