Dec 11th, 12:00 AM

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Short Paper

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Abstract

This study introduces the IT Occupation Vision, a new conceptual and methodological framework, to examine structural changes in IT occupations. It also highlights the role of industry discourse in shaping those changes. The approach suggests that these occupations are shaped by a latent collective consensus that influences labor market categories. Adapting Relational Class Analysis (RCA), a type of Schematic Class Analysis, the study leverages textual signals from online job advertisements to scrutinize structural changes in IT roles and skill sets. This work bridges Organizing Vision and diffusion literature with the IT workforce, providing insights into the interaction between innovation, skills, and emerging technologies. Unlike the Organizing Vision theory, which is artifact-centric, the IT Occupational Vision focuses on the labor aspects associated with these technological innovations. The study addresses gaps in our understanding of the socio-cognitive aspects of IT occupations, providing valuable insights for policies and practices in evolving labor markets.

Keywords: IT occupations, Skills, Diffusion, Occupational Vision, Schema, Text Analysis

Introduction

Trends in occupational markets show patterns of accelerated change. For instance, USA job advertisement trends in recent years have shown dramatic disruptions since 2016: 37% of the top 20 skills requested for the average job have changed over the past five years, and one in five skills is entirely new (Sigelman et al. 2022). Moreover, as digital transformation ripples out through the economy, many industry sectors are competing to attract skilled workers in Artificial Intelligence (AI) (Alekseeva et al. 2020), cloud computing, social media, and product management (Torkington 2023). In Early 2023, the USA market saw an increase in job postings seeking AI skills across all sectors, and the number of AI job postings overall was notably higher in 2022 over the prior year (Maslej et al. 2023). Similarly, COVID-19 has dramatically increased the speed at which technology is fundamentally changing business and contributing to the rate of disruption for jobs.

Technological innovation is a major driver of job and skill-accelerated change. The World Economic Forum (2020) forecasts that 85 million jobs across 26 global economies will be displaced by 2025 due to technological advancements, with a 40% shift in core skills. Moreover, for USA data, while IT occupations and IT skills are core components of those disruptions, change seems to be extended to several occupations (Deming and Noray 2020). While discussions about the job market usually focus on jobs created and destroyed (Hasan et al. 2015), understanding how jobs change is even more significant. For most workers, their job is more likely to evolve into something new rather than disappear. As a result, more workers will need to adopt new skills and commit to career-long training. Given this fast change rate of occupations' skill composition, particularly IT occupations, there is much need to understand how those processes of change are driven. Moreover, understanding the trajectories of occupational changes does not necessarily mean that in a period of disruption, all companies head in the same direction. Therefore, we need to understand the structure and evolution of Occupational Markets to account for patterns of change.

The Information Systems (IS) field has long been interested in the knowledge and skill requirements of IT occupations (Todd et al. 1995). However, existing research is insufficient in theorizing the fast changes in skill requirements and the structure of IT occupations. Most published IS-research focuses on using IT personnel as a proxy for firms' IT capabilities or adoption rates (Bassellier and Benbasat 2004; Liu et al. 2020; Tambe and Hitt 2012a) without further theorization of change within this occupational group. While some research has examined the spread of specific skill sets associated with IT roles (Atasoy et al. 2021; Tambe and Hitt 2012b; Todd et al. 1995) or the interplay between technological changes and emerging occupational identities (Vaast and Pinsonneault 2021), a holistic understanding of how IT occupations evolve remains conspicuously absent. Consequently, there is a compelling need for more robust evidence and theoretical frameworks to effectively grapple with the swift disruptions and evolving skill landscapes in IT occupations, attending to differences within this occupational group.

To address this gap, we propose to examine IT job markets through the lens of meaning structures and as an evolving socio-cognitive phenomenon (Grodal and Kahl 2017). In the proposed framework, occupations are shaped primarily by a latent consensus that defines what jobs are and what requirements (skills, tasks, etc.) connect to those jobs, constituting meaning structures. From this perspective, what companies know about IT occupations and related requirements (such as emerging technology like AI) resides in these meaning structures, and their understanding of the markets evolves when those structures change. By focusing on these shared meaning structures by companies looking for employees, we offer a new analytical perspective to understand the processes companies engage in when updating skill requirements to adapt, innovate, and learn. Since discourse is a vehicle where meaning-making and construction of market categories are usually analyzed (Kennedy 2008), this ongoing research examines: How can the profile of IT occupations evolve over time, and how can industry discourse shape this evolution? Consequently, this perspective explores sense-making practices driving IT occupational change with analog processes studied in the diffusion literature (Miranda et al. 2015; Swanson and Ramiller 1997).

Building on contemporary research on Organizing Vision theory and diffusion of IT (Miranda et al. 2015; Swanson and Ramiller 1997), we introduce a new construct and framework named IT Occupational Vision. We define the concept as a community idea for integrating information technology talent in organizations. Unlike the Organizing Vision, which is artifact-centric, the IT Occupational Vision shifts the focus to the labor aspects associated with these technological innovations. We argue that similar sense-making processes related to IT innovations underlie new occupational profiles' definition and legitimation, especially in environments of rapid technological change. We analyze the IT Occupational Vision as a cultural schema, grounding our approach in schema theory (Boutyline and Soter 2021), a socio-cognitive framework that elucidates that individuals and groups categorize information through shared understandings or implicit networks of concepts. We argue that these schematic representations are socially shared and manifested in the ongoing IT occupation discourse. By doing so, we pave the way for employing Schematic Class Analysis techniques to mine latent, coexisting definitions of IT occupations that can evolve. Therefore, offering a conceptual and methodological approach to examine IT Occupational Vision at scale.

To operationalize this concept, we use online job advertisement data to develop a measurement of IT Occupational Vision structure. As a form of archival materials, job advertisements "contain classificatory statements that invoke fundamental distinctions between classes or categories of things" (Ventresca and Mohr 2017, p. 821). Job vacancy data is ideal for measuring the changing skill requirements of jobs, as they directly measure employer demand for specific skills, and vacancy data are sufficiently detailed to measure changing skill demands within occupations over time (Deming and Noray 2020; Horton and Tambe 2015). Consequently, we adapt Relational Class Analysis to identify the structural properties of an IT Occupational Vision on time and to inspect the content of diverse schematic representations coexisting over time.

Conceived this way, the IT Occupational Vision can shed new light on changes within a focal occupational group and connect those changes to mechanisms in the diffusion literature. Diffusion can be understood as a categorization process where "actors jointly construct an understanding of the appropriateness and worth of some practice" (Strang and Meyer 1993, p. 489). Therefore, during times of change, firms contribute and mobilize an Occupational Vision to deal with the uncertainty created by disruptive technology and new work practices. In the rest of the article, we propose a theoretical and methodological strategy to capture the Vision and its structure, contributing to a foundation for a novel framework to examine the IT workforce.

This paper is structured in the following way: First, we introduce the concept of IT Occupational Vision and how it is structured. Then, we outline our methodology, focusing on schematic analysis designed to leverage job advertisement data. Finally, we outline the next steps and limitations.

This research has three main potential contributions to the literature on IT occupations and IT diffusion. First, we introduced a new theoretical and methodological approach to understanding IT occupations through the concept of IT Occupational Vision. This perspective provides a vocabulary and tools to explain the dynamic structures of occupations and the shifts they undergo in response to skill disruptions and evolving diffusion patterns. Second, the proposed framework and methodological tool have the potential to provide rich contextual analysis regarding skill composition in the IT occupational market, thus enabling the assessment of change patterns within occupational groups. Unlike prior IS-research that has analyzed skills spread individually (Tambe and Hitt 2012b), our approach to skills is relational, focusing on the diversity of skill compositions within occupations. Third, we aim to demonstrate the viability of using the Schematic Class Analysis approach in surfacing disparate schemas, thereby informing interpretations of occupational structure and community-level changes over time.

Theory: Defining the IT Occupational Vision and Schema Theory

First, we introduce the construct of the IT Occupational Vision and as a potential framework for explaining job structure and change dynamics. The construct builds upon the well-established Organizing Vision theory (Swanson and Ramiller 1997), native to the IS literature. Also, we employ Schema Theory (Fiske and Taylor 1991; Goldberg 2011) to describe the cognitive structure of the Occupational Vision, identifying its key components. A summary of these definitions can be found in Table 1 for easy reference.

Drawing extensively from contemporary research on Organizing Vision structure and diffusion for IT innovations (Miranda et al. 2015; Swanson and Ramiller 1997), we define the construct of IT Occupational Vision as a community idea for integrating IT talent in organizations. The Vision is a shared understanding (DiMaggio 1997) that a collective has regarding the nature and utility of IT talent for organizational operations and strategies.

Much like the Organizing Vision, the Occupational Vision is a collection of ideas developed by community members. It facilitates the diffusion of occupations by legitimizing, interpreting, and mobilizing associated activities. For organizations seeking to navigate the fast-changing landscape of IT occupations, the Occupational Vision offers a comprehensive outline of the benefits, drawbacks, and strategies for integrating various job profiles and staffing practices. Companies can contribute to elaborating an IT Occupational Vision through engagement in envisioning practices (Nandhakumar et al. 2013) to define IT talent, such as through human resource planning, staffing and recruiting positions (Oehlhorn et al. 2020). Similarly, companies can draw from an existing Vision through activities like job analysis, examining competitor preferences (Liu et al. 2020), as well as signals from occupational communities (Abbott 1993).

However, unlike the Organizing Vision, which focuses on innovative artifacts, the proposed construct of the IT Occupational Vision focuses on the labor associated with these innovations. It clarifies how specific IT roles are perceived, defined, categorized, and valued by communities, basing these definitions on essential skills and expertise. A crucial part of our approach involves examining how companies describe these roles in their public job postings. The aim is to gain a well-rounded understanding of the Occupational Vision, capturing its subtleties and complexities.

Moreover, like the Organizing Vision, the Occupational Vision is not static. It evolves through community discourse and practical experiences, leading to varying levels of agreement over its key components. Such fluidity is especially pertinent in the fast-paced world of IT, where rapid changes in required skills occur. Consequently, inspecting its dynamism allows us to study the breadth of coexisting viewpoints over time and examine their causes and impacts further. Hence, this approach is suitable for investigating shifts in both traditional and emerging IT roles, offering new perspectives on the diversity of interpretations that can coexist within an occupation over time.

Recent studies have emphasized the role of the internal structure in capturing Vision's diversity and cohesion (Miranda, Tian, et al. 2022; Miranda et al. 2015). Miranda et al. (2015) utilized Schema Theory to identify the cognitive elements structuring a Vision. According to Fiske and Taylor, a schema is "a cognitive structure that represents organized knowledge about a given concept or type of stimulus" (1991, p. 140). DiMaggio (1997) extended this definition from an institutional perspective, stating that schemas operate as "knowledge structures" that provide default assumptions under conditions of incomplete information (p. 269). Furthermore, specific types of schemas, known as cultural schemas, are "socially shared representations deployable in automatic cognition" (Boutyline and Soter 2021, p. 735). Thus, a schema becomes cultural when it is a shared cognitive structure and diffuses through social learning. Similarly, when communities build and share schemas, they build a shared understanding of what should and should not be tied together at a point in time or context (Goldberg 2011). To understand occupational phenomena, we adopt this approach, focusing on the social aspects that shape and update mental representations.

This study	Cognitive building blocks
IT Occupational Vision: Community idea for the integration of information technology talent in organizations for a focal occupation.	Higher-order, abstract schema.
Vision-in-use: a concrete, lower-order schema that a community member activates from the existing repertoire of requirements furnished by the community's Occupational Vision.	Concrete schemas represented in actors' instantiation of the community vision in discourse about a job posting.
Skill categories: Knowledge and task requirements, including IT and non-IT skills.	Components in which schemas are constructed.

Table 1. Defining IT Occupational Vision and its Structure

From this schematic perspective on occupations, we identify the cognitive building blocks that structured it, offering a lexicon highlighting its structural principles and levels (Table 1). Adapting from the levels of abstraction used by Miranda et al. (2015) in analyzing innovations, we differentiate between higher and more concrete levels of defining the occupational focus. For the highest level of abstraction, we define the IT Occupational Vision as the community idea for integrating information technology talent in organizations. Skill categories, including IT and non-IT skills requirements, constitute this schema's components. We conceive skills as knowledge and task-related associations to an occupational role.

Building upon Miranda et al. (2015), we introduce *Vision-in-use* as a concrete, lower-order schema that a community member activates from the existing repertoire of skill requirements furnished by the community's Occupational Vision. These concrete schemas are closer to actors' instantiations of the community vision in discourse expressed in discursive acts (or, in this context, the job advertisement). Over time and across different contexts, multiple Visions-in-use can coexist within a singular Vision's structure.

For example, using the Data Scientist as a focal IT occupation, we could identify the development and legitimation of a Vision for Data Scientists in the market since its beginning in 2010. However, simultaneously, as a popular and dynamic new occupation, multiple Visions-in-use are expected to coexist and dispute over time. While some employers prioritize specialized profiles, others prefer a more generalist approach. Similarly, some would prioritize support roles and other leadership roles. Some would prefer general cognitive skills, while others would prefer workers skilled in specific software. Those Visions-in-use will assemble skills in distinctive ways. We can, therefore, identify the characteristics and prevalence of such Visions-in-use over time to describe changes in the overall Occupational Vision of what the role of a Data Scientist entails. Those changes could reflect actors' opportunities to legitimize and mobilize certain actions, such as training programs, certifications, and organizational practices.

In summary, the IT Occupational Vision is a higher-order, community-shared schema within which various lower-order Visions-in-use can coexist. These are activated based on the existing skillset detailed in the community's Occupational Vision and are often expressed through discourse acts, such as job postings.

Methodology

This methodology section details our approach to studying Vision structure by adapting Schematic Class Analysis techniques for job posting data. Various archival materials have been used to study meaning systems (Ventresca and Mohr 2017), assessing relevant features of shared understanding and collective meaning that condition how organizational actors interpret and respond to the world around them and measure essential properties of these ideational systems. Specifically, we focus on job advertisement data as a speech act that signals companies' views on talent. Although our methodology is presented in a linear fashion, it should be noted that the research process is iterative, aligning with recent advancements in computational methods for theory discovery (Miranda, Berente, et al. 2022).

Context and Data: Burning Glass Technologies Job ads data of the USA Market

The primary data source is employment vacancies of the USA provided by Burning Glass (hereafter, BG), an employment analytics firm. The database contains information pulled from millions of job postings compiled from more than 50,000 sources (e.g., job boards, employer sites, newspapers, and public agencies) from 2010 to date in monthly measurements with time stamps. BG applies an algorithm to the raw scraped data that removes duplicate postings and parses the data into a number of fields, including job title and six-digit Standard Occupational Classification (SOC) code, industry, firm, location, and education and work experience (Deming and Noray 2020). The SOC Code system is a federal statistical standard used to classify workers into occupational categories to collect, calculate, or disseminate data. The SOC code can be contrasted to the actual job title in the job posting. In addition, the dataset has a high level of granularity regarding unique skills, which are combinations of knowledge, skills, and abilities listed in the job postings. Also, regarding skill data, there are over 32,000 unique skills in the database, with new ones continually added. They are tokenized, maintaining close semantic information from the original text, and nested on BG-offered clusters or taxonomy. From this data, we can measure how widely dispersed skills are and whether skills are new and/or emerging.

In this project, we focus on the traditionally defined IT occupations as a subsample of the USA job Market data. The USA is an illustrative case, as there is substantive evidence of changes in the workforce and the representativity of online job vacancy data such as BG (Deming and Noray 2020). Based on the SOC Code system, we used SOC Code 15-1200 – "Computer Occupations", which is a Minor Occupation level code within the "Computer and Mathematical Occupations" Major Occupation Category. According to USA census data, there are 4,358,410 total employees classified in this occupation in the USA, with an average Hourly Wage of $45.01 and an average Annual Wage of $93,620 (SICCODE.com 2020). SOC Code 15-1200 includes jobs that have been traditionally studied as IT- Occupations in the IS literature (Bassellier and Benbasat 2004; Tambe and Hitt 2012a, 2014; Todd et al. 1995). Noticeably, prior studies on skill disruption using BG data (Deming and Noray 2020) identify that Computer and Mathematical Occupations, defined by SOC code, are one of the main occupations that experienced skill change between 2010 and 2020. Similarly, others have found that they are one of the core occupations associated with AI-related skill requirements (Alekseeva et al. 2020).

We built upon prior skill taxonomies used in the literature on occupational studies and job markets. Each job posting in the Burning Glass database is associated with a set of skills. BG groups these skills into skill clusters. Using BG data and in coherence with the literature, Deming and Noray (2020) used a taxonomy of 12 skills (Based on Deming and Kahn 2018), where 5 of those are specifically IT-related. Non-IT skills include skills: social, cognitive, character, management, finance, customer service, creativity, and business systems. More IT-centric skills within this taxonomy include technical support, office software, specialized software, data analysis, Machine Learning / Artificial Intelligence (ML/AI). Given the relevance and spread of ML/AI skills, we refined the categorization of AI skill requirements even further, using more recent classifications from posting data (Alekseeva et al. 2020; Maslej et al. 2023). The list includes about 350 unique skill terms, including broad areas (e.g., "Natural Language Processing") to specific techniques (e.g., "Word2Vec") or toolkits (e.g., "Microsoft Cognitive Toolkit").

Measuring IT Occupational Vision as Schemas

Defining the IT Occupational Vision as a cultural schema or the idealized meaning of IT personnel, we rely on prior operationalizations of Schematic Class Analysis (Boutyline 2017; Goldberg 2011). The aim of using this analytical approach is to clearly identify the latent shared ways that job roles in IT are framed. In our context, Visions-in-use serve as a tangible type of schema present in discourse and corresponds to the schematic classes we aim to identify. Thus, Schematic Class Analysis becomes a useful tool for identifying and measuring the Vision's structure by estimating the schematic classes present in the job posting data.

Cultural schemas represent latent, shared frameworks for evaluating or organizing attributes within a particular domain (Boutyline 2017; Goldberg 2011). At the level of individual observation units, selection patterns reflect these schemas formed through a limited set of schematic transformations. Units that construct their attribute patterns from the same schema are said to belong to the same schematic class. Therefore, to gauge the extent to which these schemas are shared among different units, we measure their schematic similarity. This is captured by examining the associations between beliefs or knowledge components—in this context, skill categories—across different observation units. Applying this measure of schematic similarity to all pairs of observation units allows us to generate a similarity matrix. We then use a partitioning method to divide this matrix into higher and lower similarity areas. This approach estimates the schematic classes in the data, providing valuable insights into the content of shared cultural schemas.

While originally developed for survey-based research, Schematic Class Analysis (Boutyline 2017; Goldberg 2011) has been adapted to text-data using the word and document structure for analysis (Miranda et al. 2015). As noted, job postings provide a rich, textual representation of employer needs and expectations. In our study, the individual job posting serves as a straightforward unit for analysis. We introduce the Skill Signaling Rate (SSR), to quantify the importance of each skill category (such as "AI" or "social" skills within a given job posting. We developed the SSR as it provides a nuanced view of the relevance of specific skills in the IT job market and can be adapted to a specific skill taxonomy. This metric also accounts for the frequency of each skill category appearing in job postings. To calculate SSR, we employ a two-step normalization process: First, we adjust the frequency of each mentioned skill concerning its overall mention across all job postings. This adjustment accounts for skills that are generally more common. Second, we gauge the importance of each skill within an individual job posting by dividing the normalized mention count of a specific skill category by the sum of all normalized skill mention counts for that job posting. Our approach is aligned with the four essential guidelines outlined by Goldberg (2011): (1) the data are operationalized as scaled variables; (2) scales are ordinal and equidistant; (3) variables (here, the n number of skill categories depending on the taxonomy) are comparably scaled; (4) the scales range from zero to one.

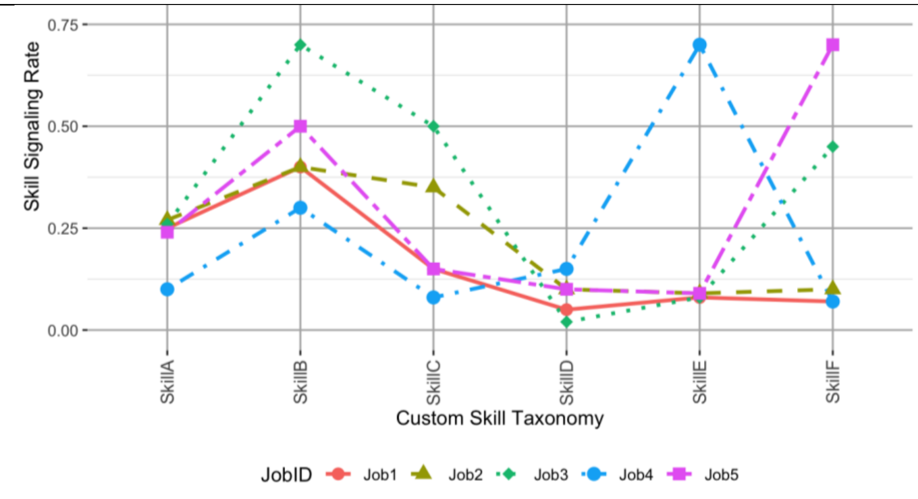

Figure 1. Skill Signaling Rate for five "Software Developer" Job Postings

As an example of how SSR and Schematic Class Analysis function in the job posting data, Figure 1 displays SSR scores for five job postings, all referring to the Software Developer Role and containing six categorized skills (for illustration, let's say SkillA = "Development Tools," SkillB = "Social Skills," SkillC = "Technical Support Skill," etc.). Figure 1 reveals that jobs vary in skill emphasis. For instance, SkillA (here, Development Tools) holds consistent importance across most postings but less in Job4. On the other hand, SkillD, generally less significant, gains prominence in Job4. This could indicate different organizational priorities or role specifications.

Regarding skill composition, Figure 1 shows unique skill sets for Job4 and Job5, as both these job postings emphasize specific skills (SkillE for Job4 and SkillF for Job5) far more than other jobs, suggesting specialized roles. Compared to other jobs that indicate a more generalist approach. Our methodological choice of Schematic Class Analysis can enhance this nuanced understanding of combinations at scale, which excels in revealing such patterns. Therefore, accounting for diversity within the same category.

Schematic Class Analysis and Relational Class Analysis Steps

Schemas have been operationalized widely in social research (Boutyline and Soter 2021). Goldberg's (2011) Relational Class Analysis (RCA) is a popular way of conducting Schematic Class Analysis. RCA is a three-step process. First, a relationality coefficient between each pair of observations is computed. The relationality coefficient signifies the schematic similarity between pairs of observations. In this context, this relationality measure provides insight into the similarity of two job postings, specifically in how they emphasize and weigh different skill categories.

The second step entails the identification of schematically similar groups. Schematic similarity can be used alongside Newman Community Detection algorithms to build network structures based on modularity maximization. We create a network where each job posting is a node, and relationality values form the edges between nodes, and filter edges in the network based on statistical significance using bootstrapping with 1,000 iterations. The algorithm consequently identifies the schematically similar clusters.

The third step involves representing schematic classes (Visions-in-use) as graphs. The graphs can depict correlations between classes of properties of schemas connecting to other classes depicted as lines connecting nodes, and they can depict classes that bind together other classes in a schema. Goldberg (2011) recommends using a graphical representation of clusters visualizing two characteristics of the relationships among variables in a schema (an illustration is available in the appendixes). Cluster graphs and distribution can assist in interpreting, comparing, and validating Vision Structure. Therefore, the offered method can assist the interpretation of context-rich schemas, assisting the comprehension and theorization of the phenomena.

Next Steps and Final Remarks

The first step will be selecting a sample and time frame to get a comprehensive view of the phenomenon; we will analyze a random sample of 10,000 job postings specifically related to IT roles. We will sample roles within the SOC code for IT occupations. Second, following the RCA process, it will be key to represent and interpret most the prevalent Visions-in-use. Also, to validate those schematic representations in contrast to traditional sub-classification of occupational groups. A third step will be comparing the prevalence of Visions-in-use over the years and interpreting subsequent emerging schemas and distributions. A related step will be providing rich forms of construct validation and legitimate interpretation. Finally, we will explore the distribution of schematic representations across industries, companies, and years. This step will require integrating firm metadata from COMPUSTAT to provide a more nuanced understanding of the employers' characteristics. These inquiries aim to extend insight into other dimensions, such as industry specificity, the influence of particular technologies, and organizational characteristics.

This study can have the following impacts on future research. First, researchers can use the theoretical and methodical model to explore antecedents and impacts of changes in occupational structure. The article provides construct clarity on the structure and the components of the Occupational Vision. The construct can be used to explore new avenues to understand their immediate antecedents and impacts. Second, this contributes to theory by building connections from Organizing Visions and managerial fashions literature (Miranda et al. 2015) to the stream of the IT workforce. Similarly to Miranda et al (2015), we can create more specific measures regarding the attributes of the Vision's Structure using the schematic analysis information, such as measures of diversity or consistency. In the context of the diffusion of social media, they use this measurement to predict the demand for innovation. Consequently, future research could build on this strategy in the context of occupations and explore bivariate relationships between these attributes and the demand (popularity or salary) of focal jobs. Potentially examining diffusion dynamics in the context of job markets based on institutional pressures and learning. Finally, from a practical standpoint, the direction of this research can aid both firms and workers by shedding light on the most significant changes in job roles and skill sets, thus informing better policy decisions for workforce preparation.

There are important limitations of this approach that should be acknowledged and that hopefully can lead to future research on IT occupational structure and diffusion patterns. First, the limits of the generalizability of the research findings will need to be further discussed and examined regarding data and the selected approach. While job advertisement data has proven insightful about the US job market (Deming and Noray 2020), online job vacancies are not an expanded practice in all countries. Moreover, it may not fully capture all elements of the job market, such as informal hiring channels or internal staffing. That said, international organizations are increasingly interested in exploring its value across regions (Bennett et al. 2022). Also, the method proposed here creates a conceptual and methodological approach to different occupational and skill taxonomies. Its usefulness will depend on examining standardized taxonomies and the emerging unstructured content from job advertisements. Second, the model does not empirically show a strategy to analyze how task alteration driven by emerging technology implementation could affect vision structure. Future research can unpack processes in which task alterations induced by the presence and implementation of emerging technologies can have over the schematic definition of IT occupations. Organizations must recombine and adapt emerging technologies while requiring new skills to innovate, learn and adapt to evolving technological environments. Consequently, emerging technologies can change knowledge codification for productive and innovative activities in organizations, shaping occupational markets. Alterations in task structure can come from the elimination or addition of tasks, as well as the diminution or intensification of tasks (Hollister et al. forthcoming). Therefore, future research can explore the connection between specific technology-driven change and occupational structure.

Our research introduces a novel approach to understanding IT occupations, particularly during skill shifts. We introduced the concept of IT Occupation Vision and a methodological strategy to measure it through Relational Class Analysis (RCA) using job posting textual data. The approach is versatile and can be applied to other occupational groups to understand changes in structure over time, highlighting the role of industry discourse in shaping this evolution.

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