One Size Does Not Fit All: Global Perspectives on IT Worker Turnover

Benjamin Yeo, Alexander Serenko, and Prashant Palvia

***Abstract*—Although the IT workforce has become increasingly global, much of the research on issues related to IT workers published in leading academic journals is conducted in the U.S. However, the majority of the world does not share the same context as the U.S. Despite that, comparative studies exploring country differences rarely demonstrate how and why these differences occur on a global scale. By relying on a dataset based on a survey of more than 10 000 IT workers in 37 countries, we employed the decision tree technique to build an accurate model of IT job turnover in the U.S. We then applied this model to 36 countries to test whether it is more accurate in countries that are similar to the U.S. in terms of their geographical proximity to the U.S. and the proximity of their cultural, political, and labor market contexts. The findings demonstrate that while the U.S. model of IT job turnover is not necessarily less accurate for countries that are geographically farther from the U.S., it is less applicable in the countries with cultural, political, and labor market conditions different from those of the U.S. Thus, global IT managers are recommended to interpret the U.S.-centric literature with caution.**

***Index Terms*—Global IT, IT workers, job turnover, the World IT Project.**

I. Introduction

The dawn of the 21st century has transformed the nature of the IT workforce into a unique, multinational, global enterprise, where IT employees that work for the same company are often located in different parts of the world. As a result, business managers, especially HR professionals, have to account for various countries' idiosyncrasies when interacting with their nondomestic IT workers. For instance, many major IT companies—such as IBM, Google, Facebook, Tata Consultancy Services, and Amazon—need to simultaneously manage their IT workforce located in different countries that have unique cultures, political systems, and labor market conditions. Fortunately, to support their evidence-based decision-making strategies, global IT managers can rely on a substantial body of knowledge that is documented in numerous academic publications and delivered to busy practitioners through professional magazines, books, meetings, and industry forums. IT management is both a science and a profession, and IT research findings can be used to solve a myriad of problems for corporations and organizations [1]. The problem, however, is that most IT workforce research is largely U.S. dominated [2], and these U.S.-based academic findings and corresponding recommendations may not be directly applicable to all countries [3]. Furthermore, they may be more applicable to some countries than others.

People living in different countries often exhibit some similar traits, attitudes, and behaviors which allows researchers to develop frameworks, theories, and principles that are generalizable across different countries to a certain extent. At the same time, people from different countries often vary on a number of behavioral and psychological dimensions [4], which makes the U.S.-based recommendations less generalizable on a global scale. This is akin to Lee and Baskerville's [1] conceptualization of generalizability from theory to description whereby findings from one context are tested in another. However, the validity of this application in different contexts is questionable because there may be extraneous factors beyond the scope of the original application, and it is a fallacy to assume the universal nature of a theory.

Different contexts contain idiosyncrasies that are not easily replicable. For example, results from a survey on recent graduates' career aspirations are likely to differ among countries because of graduates' unique expectations and diverse job market conditions. Wage expectations are context dependent due to job seekers' biases, optimism, preferences, etc. Thus, applying one context's preference to set wages in another may lead to misrepresented realities and incorrect decisions [5]. Moreover, Henrich et al. [5] demonstrate that about 12%, an overwhelming minority of the world's population, is WEIRD (Western, Educated, Industrialized, Rich, and Democratic). They are outliers in the world because they have been found to be psychologically unusual compared to the remaining 88% that do not share these five characteristics. It follows that individuals residing in Western countries—in particular Americans—differ from their non-Western counterparts in terms of their values, reasoning, and behavioral characteristics. Research shows that Americans utilize more analytical thinking than Europeans, while Asians use holistic reasoning more by considering stakeholders' behaviors, due

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to their different culturally constructed environments [5]. Such differences are remarkably evident in the workplace context: for example, Japanese IT employees rely on mutual cooperation, emphasize organizational commitment, embrace the notion of long-term employment, accept a bureaucratic management style, and adhere to a rigid hierarchical structure of their domestic IT industry [6], [7]. By contrast, such mentality and corresponding management principles are virtually nonexistent among American IT workers who live and work in a highly individualistic cultural environment. And yet, the majority of empirical studies on the IT workforce published in leading peer-reviewed journals are conducted by Western researchers who rely on data samples collected in Western countries [2]. As a result, conclusions and recommendations documented in Western-context works may not be universally applicable across the world, and generalizing from Western contexts may lead to mistakes.

Taken together, it is likely that an over-reliance on Western (in particular, the U.S.) samples significantly limits our global understanding of IT workers and poses challenges to managing them across different countries of the world. While previous studies have shown that IT workers' issues differ across countries [9], [10], we are unaware of any that demonstrates the quantitative extent of these differences, as well as how and why these differences occur. Furthermore, to fully demonstrate the how and why, we use comparable data on 37 countries. Regardless, while IT researchers realize the relevance of different contexts, they continue to seek generalizability as their ultimate goal [11], particularly because IT research has direct applications to the IT profession [1].

To this end, we respond to the call to empirically test the applicability of U.S.-centric findings to other populations, especially those that are not WEIRD [5]. The research question is: *To what extent are U.S.-centric findings applicable globally?* We use the Gravity Model to frame the investigation and make three contributions to the literature. First, by answering this question, scientific and practitioner IT communities will be able to better assess the applicability of recommendations and conclusions reported in Western contexts to their specific countries. Second, our scientific inquiry serves as an impetus for more research from non-Western perspectives, toward a more balanced view of IT work and worker issues. Third, we demonstrate that the Gravity Model, an Economics theory, can be extended and applied to study management issues in global IT research.

To address this research question, we built an accurate model that predicts IT job turnover in the U.S. Next, we applied the same model to 36 countries to assess the accuracies in predicting their respective IT job turnover. Finally, we analyzed how these accuracies vary with each country's geographical, cultural, political, and labor market differences from the U.S. Our findings corroborate the literature and demonstrate that job satisfaction [12], work overload [12], personal accomplishment [13] and job insecurity [14], [15] predict IT job turnover among IT workers in the U.S. well. However, the same model in other countries yields different accuracies: the more different countries are from the U.S. in terms of their cultural, political, and labor market characteristics, the less accurate the model is in predicting IT job turnover. Thus, global IT managers must interpret the U.S.-centric literature with caution.

The article is structured as follows. In Section II, we discuss the Gravity Model as a theoretical framework for the study. In Section III, we discuss job turnover, an important IT issue that is used to assess the applicability of U.S.-centric findings around the world. In Sections IV and V, we explain our methodological approach and the decision tree technique, respectively. In Section VI, we test the model of IT job turnover in the U.S., and in Section VII, we retest it outside the U.S. We discuss our findings in Section VIII and conclude the article in Section IX.

II. Gravity Model

The Gravity Model may shed some light on this concern. As a theory in Economics, it suggests that the volume of trade, migration, traffic, investment, etc., between two countries depends on the geographical distance between them: the closer they are, the more exchange is expected to take place; but with distance, the volume of exchange should decline [16].

Based on literature review and to the best of our knowledge, the Gravity Model has not been applied in management research. However, by following this model's line of reasoning, it is logical to assume that the degree of applicability of U.S.-based academic findings also depends on the country's geographical proximity to the U.S. The rationale is that a high volume of trade, migration, traffic, investment, etc., between two countries may shape people's preferences, attitudes, behaviors, social norms, and, most importantly, occupational cultures by making them more alike. The generalizability of U.S.-based findings would thus depend on the degree to which the attributes of employees in the other countries—which are determined by geographical distance in this case—are similar to those of U.S. workers. For instance, U.S.-based recommendations should be more applicable in Canada than France due to the former's geographical proximity to the U.S. As a result, one should expect a positive relationship between the country's geographical closeness to the U.S. and the extent of the applicability of the findings generated in the U.S. context.

In this study, we extend the notion of distance in the Gravity Model by arguing that, in addition to geographical distance, the magnitude of differences between a country's culture, political climate, and labor market characteristics and those in the U.S. may also affect the degree of the applicability of U.S.-based models of IT work in other national contexts. The rationale is that while the (physical) geographical distance between the countries is important, the emergence of recent telecommunications technologies, social media, and enterprise systems erases physical boundaries and renders geographical distance less significant. Thus, it is also practical to view intercountry distances by using other factors—like cultural, political, and labor market conditions—that can be also relevant in determining the degree of similarities to and differences from the U.S. Furthermore, we demonstrate how the Gravity Model can be extended to management research.

National culture plays a big role in influencing organizational management styles which underlines the importance of understanding cultural differences [4]. For example, companies in the U.S. tend to be less autocratic, support flexibility and task delegation, and empower lower level workers. By contrast, those in Mexico, although geographically close, favor centralized authority and limit decision-making abilities of individual employees [17]. As a result, these differences trickle down to shape IT employees' job attitudes and behaviors by making U.S. and Mexican IT workers less alike [3]. Therefore, recommendations developed by scholars who study IT workers in the U.S. are likely to be less applicable in countries that are culturally different.

The development of a country's IT industry also depends on political support. Political climates differ from country to country and they also influence IT workers' attitudes and behaviors [3]. For example, the growth of energy-efficient IT can be inhibited by political obstruction, guidelines, and policy [18]. Political factors also affect the number of jobs available and workers' decisions to switch jobs. While there is limited literature on the impact of political factors on IT job turnover, studies have shown that managerial turnover is induced by bond ratings, changes in politicians [19], and political conflict [20]. As a part of a country's political climate, the level of corruption in developing countries is higher than that in the U.S. and other developed nations. Among its consequences are the distribution of resources at the macro level which affects human capital development and income. Bribery also has a detrimental effect on the health and safety of workers [21]. IT employees in an environment with less corruption are poised to be less concerned about these factors and can devote more time and energy to work-related outcomes, enhancing their job satisfaction. On the contrary, those who are bogged down by corruption-related consequences have more concerns and may have a lower job satisfaction.

Furthermore, different labor market conditions between the U.S. and other countries translate to the differential ease with which workers can find another job [22]. In particular, market conditions influence organizational employment policies which, in turn, affect IT job turnover [23]. For instance, in 2021, the U.S. IT industry experienced a wave of voluntary resignations (i.e., the Great Resignation) [24] which created favorable job market conditions for IT job seekers [25], while this phenomenon was not observed in most Asian countries which happened, at least in part, due to different labor market conditions between the U.S. and Asia. This changed the way IT employees perceive the value of their current jobs which, in turn, affects their work-related actions, including turnover: one who has more difficulty finding another similar job is less likely to quit, *ceteris paribus*.

As such, consistent with the tenets of the Gravity Theory, it is likely that the generalizability of U.S.-based research findings depends on four factors: the country's geographical closeness to the U.S., national cultural differences, differences in political climate, and differences in labor market characteristics.

III. IT Job Turnover

To empirically investigate the proposition above, we focused on IT job turnover as a variable of interest. The selection of IT job turnover addresses three gaps in the literature. First, IT workers are critical and have considerable influence on their organizations [26]; their turnover incurs substantial costs and inhibits organization performance [23], [27], [28]. Hence, retaining them remains a vital issue today, garnering attention to IT worker retention [29]. Countries rely on the use of IT to boost their productivity [30]. IT workers possess specialized skills and knowledge (e.g., they run and maintain large legacy systems) which makes them extremely valuable to employers [31]. As a result, attaining strategic business goals depends heavily on retaining IT workers [32] because then workers leave, their critical organizational knowledge disappears [27]. In many organizations, more than one-third of the IT budget is allocated to IT worker wages. However, IT worker turnover has been and remains a major issue for senior IT management [33]. Frequent turnover among IT developers reduces overall productivity due to time needed to learn how various organizational processes work [29]. The departure of these key contributors to long-term organizational success inhibits business opportunities, such as the development and implementation of new technologies that are critical in today's competitive environment [32]. The recruitment and training costs for a new IT worker amounts to 150% of an employee's wages [33]. Despite efforts to retain them, IT workers turnover has been increasing and is predicted to reach 7% per year in the immediate foreseeable future [22]. The issue has transcended organizational boundaries and become an industry phenomenon. Furthermore, IT workers engage in occupational circles within and outside their organizations. As a result, attitudes regarding turnover can quickly disseminate and result in a turnover culture, affecting multiple organizations [32]. Thus, it is not surprising that retention of IT workers is one of the leading themes in the IT workforce literature [34].

Second, while there is an abundance of studies on job turnover, there is a lack of specific focus on global IT turnover. For instance, GLOBE, a large-scale international study that looks at cultural practices and leadership, has been applied to job turnover, among other business areas. However, this research focuses on workers in general rather on IT employees specifically [3]. We argued earlier that IT workers are critical to the strategic direction and operations of their company. IT workers possess specialized knowledge and skills, and they have different motivating work characteristics that affect their job satisfaction and turnover intentions [26]. The extent to which IT workers perceive their roles as critical to their organization is a more important motivating factor than for their non-IT counterparts, thereby influencing their turnover [31]. This means that IT employees differ from other workers with respect to their turnover, underlining the need to avoid generalizing non-IT findings to IT workers and instead, study them as a separate entity. To address this gap, in this study, we focus specifically on IT job turnover. Of note, we are not arguing that non-IT workers are all similar in this regard. Each sector may be different in various ways. Instead, our study focuses on IT workers and our argument advocates for a specific focus on them.

Third, cross-country comparisons with respect to IT job turnover have received limited attention in the literature [29]. Existing studies are usually based on a small number of countries. For example, an investigation of the turnover of software developers included 62 practitioners from India, Ireland, and North America [23]. Another comparative study between China and Japan showed that workers have different motivational work characteristics that influence their job satisfaction and turnover intentions [26]. A multicountry study on job insecurity and turnover intention showed that workers in Australia and New Zealand perceive less threat from technological disruption than their counterparts in the U.S. [35]. A project on work pressure and turnover intention found differences in the impact of work pressure between workers in Indonesia and Taiwan [4]. Our study includes 37 countries, and we go beyond cross-sectional differences to show the extent to which they differ with respect to cultural, political, and labor market characteristics.

IV. Approach

Our approach includes three steps. First, we build a model that predicts IT job turnover that is well supported in the U.S. context. This model uses data on IT workers in the U.S. and is sufficiently rigorous to predict job turnover among IT workers in the U.S. Second, we apply this U.S. model to other countries using the same independent variables to predict IT job turnover in each respective country, using data on IT workers from each respective country. Finally, we compute each country's geographical, cultural, political, and labor market differences from the U.S. and compare the accuracy of each country's prediction to each respective country's differences from the U.S. We advocate that generalizability is important in IT research. The only way to assess the generalizability of this U.S. model is to apply it to contexts where it has not been empirically tested before [1]. The juxtaposition of accuracies and four factors reflecting intercountry differences illustrates the degree of applicability of the U.S. model in other countries.

To test the extent to which U.S. findings are applicable beyond the U.S., it is important to have a range of countries from different continents and include countries that are not WIERD. As a part of the World IT Project [3], an identical survey instrument was administered to approximately 300 IT workers in each of the selected 37 countries[1] (including the U.S.) from different regions of the world, among which only eight are from North America and Western Europe. Thus, most countries in our study are developing and are not WEIRD [5]. Where applicable, the survey was translated to the employees' native language, backtranslated, and revised for validity and comparability across the 37 different countries [36]. Each respondent was at least 18 years old, and more than 50% of their work was IT-related. The entire dataset included 10 386 records collected between 2016 and 2017.

[1]In alphabetical order: Argentina, Bangladesh, Brazil, Canada, China, Egypt, Finland, France, Germany, Ghana, Greece, Hungary, India, Iran, Italy, Japan, Jordan, Lithuania, Macedonia, Malaysia, Mexico, New Zealand, Nigeria, Pakistan, Peru, Poland, Portugal, Romania, Russia, South Africa, South Korea, Taiwan, Thailand, Turkey, U.K., U.S., and Vietnam.

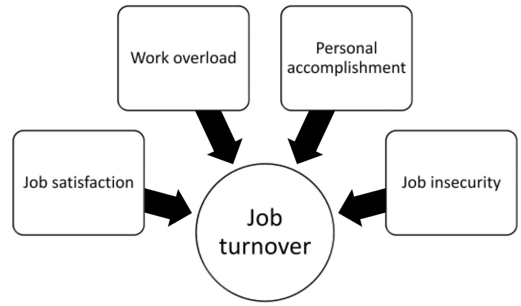

Fig. 1. Common predictors of IT job turnover.

In our U.S. model, we positioned job satisfaction [23], [27], [28], [32], [37], work overload [32], personal accomplishment [13], and job insecurity [15] as predictors of IT job turnover because these relationships are well established in the extant literature (see Fig. 1). Job satisfaction, defined as workers' overall assessment of all aspects of their job, has been known to be a key predictor of job turnover. IT workers experiencing lower job satisfaction are expected to have higher turnover [12]. Work overload, defined as employees' perception that the amount of work exceeds their available resources, is a common issue among IT workers. IT workers do not view long working hours favorably [23] because this causes performance-related anxiety and increased pressure [4] and is a major source of stress and work exhaustion which promote employee turnover [12], [28]. Personal accomplishment refers to workers' perception of competence and achievement in their work [38]. Reduced personal accomplishment has been found to increase turnover among workers [13]. IT workers are motivated by various characteristics of their jobs [26] that are critical to their retention [23]. It is not surprising that for them, personal accomplishment is especially important, and IT workers who experience a lack of personal accomplishment are more likely to leave for greener pastures. The significance of their work is a key motivating work characteristic that reduces job turnover [26]. Job insecurity reflects workers' sense of being able to keep their job. In many countries, job insecurity has become a major concern among IT workers due to increased competition and market instability [15], as well as technological disruption [35] in today's globalized employment landscape. Job insecurity induces fear and anxiety [14], and stronger insecurity of the stability of one's job triggers turnover [14], [15], [35].

As such, the proposed predictors of IT job turnover—job satisfaction, work overload, personal accomplishment, and job insecurity—have been well established in the literature in the U.S. context. Thus, they are good candidates to test the applicability of the proposed model in diverse contexts that differ geographically, culturally, politically, and have different job market conditions.

All constructs were operationalized by using well-established instruments [3]. From the World IT Project survey data, we computed each of the predictors in Fig. 1 as a composite of individual survey items. For each item, respondents expressed their

TABLE I
CONSTRUCT DESCRIPTIONS

Construct	Definition and measurement	Alpha
Job satisfaction	IT workers' overall assessment of all aspects of their job [38]. Measured with three survey items.	0.88
Work overload	IT workers' perception that the amount of work exceeds their available resources [40]. Measured with four survey items.	0.89
Personal accomplishment	IT workers' perception of competence and achievement in their work [38]. Measured with four survey items.	0.82
Job insecurity	IT workers' sense of their job being jeopardized [14]. Measured with four survey items.	0.70
Job turnover	IT workers' intention to change jobs within the IT field [12]. Measured with three survey items.	0.79

level of agreement on a 5-point Likert-type scale. We assessed their corresponding reliabilities and found all predictors to be sufficiently reliable [39]. Table I presents their corresponding definitions, operationalizations, reliabilities, and references in the literature.

In the U.S. model, to predict IT job turnover (as explained in the following section), we computed IT job turnover as a categorical variable for each country using the corresponding country mean as the cut-off point to determine whether turnover is high or low. There are two reasons for treating IT job turnover as a dichotomous variable. First, the results become easier to interpret [41], thus increasing their usefulness [42]. This is especially important because, unlike more complex machine learning algorithms, results from decision trees should be easily interpreted and explained [43]. Second, the extent of turnover may differ for different countries due to contextual differences. For example, in Japan, a stereotypical white collar worker is expected to stay at a company throughout one's career [2], [44], making job turnover less likely than in a more individualistic culture like the U.S., where workers tend to move on to ensure future professional growth and career development. Thus, it is more appropriate to interpret turnover scores within each country's context rather than universally.

V. DECISION TREE

We selected decision trees as a statistical technique to test the proposed model. Decision trees are a staple of machine learning methods and have a wide range of applications. They represent a rule-based model that classifies records based on if–then rules [43]. Decision trees have a generic tree-like structure that splits the dataset from the root to several terminal nodes. The root node comprises the entire dataset used to build the decision tree. Each terminal node represents an outcome, typically "yes" versus "no" or "high" versus "low." The splits subset the data into branches and are characterized by decision rules that lead to the eventual outcome [45]. For example, assume that we have a dataset whereby each record corresponds to a day. The predictors include weather conditions, such as whether it is raining (TRUE and FALSE), the temperature (in Fahrenheit) and the court availability (TRUE and FALSE), and the outcome variable is whether or not we played tennis that day ("Yes" and "No"). A decision tree to predict whether to play tennis can be illustrated from three if–then rules: when it is not raining (condition: raining = FALSE), temperature is more than 75 degrees, and the court is available (condition: available = TRUE), we play tennis (outcome: "Yes").

Our decision to use decision trees was fivefold. First, this method is particularly applicable to test cross-country differences in the proposed model because we can apply the if–then rules derived from the U.S. data to predict IT job turnover in other countries using the same variables and assess the resultant accuracies of these predictions. Second, it does not require meeting assumptions about data distributions and can handle nonlinear relationships among variables [46]. For instance, we ran a Shapiro–Wilk test on the U.S. data and established that job turnover does not satisfy the normality assumption required for a regression ($W = 0.946$, $p = 0.001$). Third, the decision tree technique handles nonlinear relationships and does not require the researcher to specify a nonlinear model *a-priori* [46]. It illustrates relationships between predictors and the outcome via value ranges of important predictors, thus adding depth to the analysis. For example, it can show that when variable x is between 3 and 5, the outcome is "yes," and when it is between 5 and 7, the outcome is "no." Fourth, decision trees work well with redundant predictors that do not show up in the tree if they are found to have little influence on the outcome [47]. Fifth, even though complex machine learning algorithms are widely used today, they suffer a severe limitation because of their black-box approach. This has been argued to limit their use and application because results are difficult to explain and interpret. While users are able to use the algorithm to make predictions, they are unable to explain why the outcome was predicted and how to enhance it further. Unlike these complex algorithms, decision trees have an advantage because they are more transparent, making it easier to explain and interpret the findings [43]. The results can also be presented visually for nontechnical audiences [48]. In addition, decision trees have been found to be more stable than complex algorithms such as multilayer artificial neural networks [49].

VI. IT JOB TURNOVER IN THE U.S.

For the U.S., the decision tree performed well, with a 73.3% accuracy in predicting IT job turnover, and the most important predictors are job satisfaction and job insecurity, as shown in the splits (see Fig. 2). The decision tree is also well poised to differentiate between high and low turnover using the predictors (Area under the Receiver Operator Characteristics Curve, AUC = 0.699). The oval represents the root node that comprises all records in the U.S. dataset. The arrows represent the branches, or paths, from the root node to each node represented by rectangles. Each node contains a subset of the records from the preceding node. The shaded rectangles denote the terminal nodes, where there are no other rules to further split the dataset into subsets.

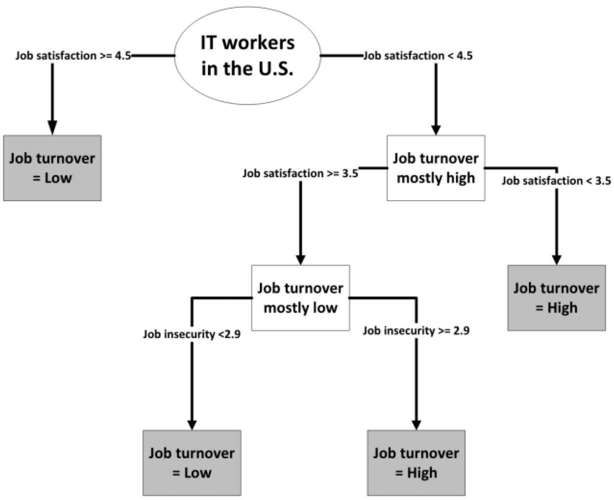

Fig. 2. Decision tree for IT job turnover in the U.S.

TABLE II
DECISION TREE RULES FOR IT JOB TURNOVER IN THE U.S.

Rule	Description	IT Job Turnover
1	Job satisfaction >= 4.5	Low
2	Job satisfaction >= 3.5 and < 4.5, and Job insecurity < 2.9	Low
3	Job satisfaction >= 3.5 and < 4.5, and Job insecurity >= 2.9	High
4	Job satisfaction <= 3.5	High

TABLE III
CONFUSION MATRIX FOR THE U.S. DECISION TREE

	Actual High	Actual Low
Predicted High	65	26
Predicted Low	56	160

Here, additional splits will not increase the accuracy of the prediction [42].

Table II shows the decision tree rules for the U.S. Following the decision tree from top to bottom (see Fig. 2), in Rule 1, when job satisfaction is more than or equal to 4.5, turnover is low. Rule 2 shows when their job satisfaction is more than or equal to 3.5 and less than 4.5, and job insecurity is less than 2.9, IT workers have low turnover. Following Rule 3, when job satisfaction is more than or equal to 3.5 and less than 4.5, and job insecurity is more than or equal to 2.9, turnover is high. Rule 4 shows when an IT worker's job satisfaction is less than 3.5, turnover is high.

Table III shows the resultant confusion matrix which describes the actual and predicted outcomes of the decision tree. The values are used to compute the accuracy and various metrics of the decision tree. Out of the 307 U.S. IT workers, the decision tree predicted 225 correctly (65 high and 160 low); hence, the accuracy is 73.3% (225/307). Out of 121 U.S. IT workers who experienced high IT job turnover, the tree predicted 65 correctly [True Positive Rate or sensitivity = 65/(65+56) = 0.537]. Likewise, out of 186 IT workers who experienced low turnover, the tree predicted 160 correctly [True Negative Rate or specificity = 160/(26+160) = 0.860]. Precision measures the accuracy of all its high turnover predictions, while negative predictive value measures the accuracy of all its low turnover predictions. Although the decision tree performs better at predicting low IT job turnover (given its higher sensitivity), the quality of its predictions for both high and low turnover are almost equally good [precision = 65/(65+26) = 0.714, negative predictive value = 160/(56+160) = 0.741].

VII. PREDICTING IT JOB TURNOVER IN OTHER COUNTRIES

Next, we applied the U.S. decision tree to other countries to determine the extent to which it applies in the other 36 countries: the higher the accuracy, the more applicable the U.S.-based model is. By applying the U.S. decision tree to each of the 36 countries, we obtained the corresponding accuracies of the U.S. model from the resultant 36 confusion matrices. To test the effect of geographical distance, we mapped each country along two dimensions—predictive accuracy and geographical distance from the U.S. (in km)—and generated the Spearman's rank-order correlation coefficient. We used Spearman correlation because of the small sample size. Surprisingly, we did not observe a statistically significant relationship between predictive accuracy and geographical distance from the U.S. (ρ = –0.24, p = 0.160), i.e., being geographically closer to the U.S. did not imply more similar experiences in the predictors of IT job turnover. This means there are countries that are geographically far from the U.S. where the model can be applied to predict IT job turnover more accurately than in a country that is closer. For example, the accuracy of the U.S. model is more accurate in Greece (accuracy = 72.64%) than in Canada (accuracy = 71.10%).

Following which, we repeated the analysis using a country's national culture, political climate, and labor market characteristics. For cultural differences, we relied on Hofstede's cultural dimensions—Individualism versus Collectivism (the extent to which individuals are integrated into groups or the degree of looking to oneself as an individual versus the collective), Uncertainty Avoidance (the extent to which individuals prefer unambiguous, clear, and well-structured situations), Power Distance (the degree of acceptance that power is not distributed equally), Masculinity versus Femininity (the distribution of gender roles whereby those on the masculine end value assertion and competitiveness while those on the other emphasize modesty and caring values), and Long-Term Orientation (one's perception of the future versus the present in various situations). These are well established in IT research to capture international cultural differences [3]. We measured political differences in terms of a country's rule of law index, government effectiveness index, control of corruption, regulatory quality, voice and accountability, political stability, corruption perception, political rights, civil liberties, and the number of women in parliament [50]. These measures were based on each country's government characteristics that reflect the political context of each country. For labor market characteristics, we used unemployment and labor force participation rates [50].

We used corresponding variables in each context to create three vectors for each country. Each country's culture vector comprises scores from the five elements that correspond to Hofstede's five cultural dimensions [3] used to characterize a country's culture. Likewise, the political climate vector of a country comprises the country's scores from all the ten items that characterize a country's political climate. The same applies to the labor market vector that comprises unemployment and labor force participation rates.

We then computed each vector's difference from its corresponding U.S. vector using Euclidean distance that illustrates the extent of differences between the country and the U.S. Euclidean distances are a conventional method based on Pythagorean theorem and are measured as the length of a straight line between two points using cartesian coordinates. It is akin to the length of the hypotenuse of a right-angled triangle in a two-dimensional space. In a multidimensional space, it is measured as the length of the line segment between two vectors. For instance, the cultural difference between France and the U.S. is the Euclidean distance between their respective cultural vectors. For two vectors (x_1, y_1, z_1) and (x_2, y_2, z_2), where x_n, y_n, and z_n are numerical, the formula to compute the distance, D, between the two vectors is given in (1). This approach allows us to determine the extent of similarities and differences across these characteristics among the countries

$$D = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2 + (z_1 - z_2)^2}. \qquad (1)$$

As expected, we observed that the more culturally different IT workers in a country were from those in the U.S., the less accurate and hence the less applicable the U.S. model was ($\rho = -0.39$, $p = 0.020$). For instance, the model was far less accurate for Jordan than for Finland—51.38% and 74.68%, respectively—because IT workers in the former country are more culturally different from the U.S. than those in the latter. Likewise, the more politically different a country was from the U.S., the less accurate and hence less applicable the U.S. model was ($\rho = -0.43$, $p = 0.012$). A visual inspection of the results showed that this was particularly evident for countries that are extremely different from the U.S. in this characteristic, such as Iran and Nigeria, whose accuracies were 46.78% and 40.23%, respectively. On the contrary, countries that were politically similar to the U.S.—e.g., Germany and Canada—had accuracies of 73.65% and 71.10%, respectively. It follows that political climates affect how IT workers perceive job expectations in the U.S. versus other countries. This, in turn, explains why a U.S.-based model of IT job turnover may not apply in different political contexts.

Finally, there is also a significant negative correlation between the predictive accuracy of the model and the country's differences in terms of labor market characteristics from the U.S. ($\rho = -0.35$, $p = 0.045$). For example, the model was less accurate in predicting IT job turnover in countries such as Pakistan and Macedonia—47.47% and 64.63%, respectively—that have large differences in labor market characteristics compared to the U.S. than in Germany and Canada—73.65% and 71.10%, respectively—that are relatively similar in this regard.

VIII. U.S. Way is Not Always the Way

To address our research question, we show that U.S.-centric findings, using IT job turnover as a variable of interest, are not equally applicable globally. They apply better in countries that are more similar to the U.S. culturally, politically and in their labor market characteristics.

The U.S. model corroborates the literature on the predictors of job turnover among IT workers: job satisfaction [23], [27], [28], [32], [37] and job insecurity [14], [15], [35] are key to managing IT job turnover. However, given that the majority of the literature on IT workers is Western-centric, this corroboration stops at the U.S. borders. Recent globalization trends, which are fueled by various Internet-based technologies—in particular, email, social media, telecommuting, and videoconferencing—have somehow erased perceived communication barriers among countries, so geographical distance no longer matters as much as it did in the past. This is why the U.S. model of IT job turnover is not necessarily more accurate for countries that are geographically closer to the U.S. What does matter, however, are cultural, political, and labor market differences. Workers in more collectivist cultures maintain more harmonious relationships with their colleagues, thereby adding a social cost when they quit their jobs. This is less applicable in more individualistic cultures where workers emphasize personal achievement over relationships with their colleagues [37]. Political factors have been found to induce managerial turnover [19], [20], [51]. Furthermore, the availability of job alternatives can influence turnover intentions [37]. While there may be other contexts that can explain the nonuniversal nature of U.S.-dominated research findings [3], our analysis corroborates the literature that IT workers in different countries differ from those in the U.S. [52], and they differ in these three major ways with respect to IT job turnover.

Cross-country differences are critical to multinational corporations as they strive to retain their IT employees [4]. Managing IT workers globally requires customized approaches tailored to their local contexts [53], and U.S. management practices can be more effectively applied in countries that share similarities along these dimensions. However, the more different they are, the less applicable the U.S. model is. Thus, as our central argument, we caution against the direct universal application of U.S.-based findings and recommendations. This is especially critical today as IT work is becoming increasingly global [54]. Due to a series of recent COVID-19 lockdowns, telecommuting has quickly become widespread among knowledge workers, including IT professionals. As a result, many organizations have started employing IT personnel physically located in other countries. Our findings show that managers should keep in mind that these remote IT workers operate in their own unique cultural, political, and labor market conditions, and the more different these conditions are from those of the U.S., the less managers should rely on principles, recommendations, and practices that were developed and traditionally applied in the U.S.

However, this does not mean that the U.S.-based literature is not useful. Our results show that they are still applicable, but the level of applicability decreases in accordance with various country differences. Therefore, practitioners and researchers should adopt a more global view when applying the literature. This entails understanding context limitations and adapting U.S.-based models to local contexts, akin to translating or tailoring survey questions to different countries. *One size does not fit all, but some fit better than others.*

Reflecting on our three contributions, first, the findings show how scientific and practitioner IT communities can better assess the applicability of recommendations and conclusions reported in Western contexts to their specific countries. Pertaining to managerial implications, our findings provide empirical evidence to support localized IT worker management practices. Multinational corporations should consider relying on local IT managers to supervise their IT personnel. Local offices that cater to domestic IT workers' well-being are better than centralized head offices located in other countries. For example, even though job satisfaction influences IT job turnover, the extent to which it does varies. The negative impact of a dissatisfied IT worker may be more pronounced in some countries. Therefore, human resource policies can be localized to be sensitive to cultural and political contexts. Researchers on IT work and worker issues can reassess the applicability of recommendations and conclusions reported in U.S. contexts against different cultural, political, and labor market contexts. Second, our findings underline the importance of having more scholarly and practitioner studies from non-WEIRD countries [5] to provide more comprehensive and balanced perspectives, thereby enriching the literature on global IT work. This can help global IT managers better understand and motivate their employees. Although our study focused on IT job turnover as a variable of interest, the need for more balanced perspectives applies to other issues as well. Third, on the theoretical front, we demonstrate that the tenets of the Gravity Model can be extended and applied to explore global management issues. Future studies can utilize a similar approach framed by the Gravity Model to address other global IT work and worker issues, as well as other sectors, for example, banking and healthcare.

IX. Conclusion

Employee retention remains one of the most important issues in the IT industry [33], given the costs of the loss and replacement of vital human capital. Similar to other knowledge workers, IT employees have unique, specialized skills and tacit knowledge [32] that contribute to the growth of their companies' repository of knowledge that would otherwise be depleted [55].

Managing IT job turnover requires special attention given to IT workers' job satisfaction and job insecurity. But this is more applicable to the U.S. context. Our analysis of how the U.S. IT turnover model applies in different countries shows that it is not universally applicable and macro level contexts are also relevant, prompting a broader approach to address IT job turnover on a global scale. With the advent of outsourced IT work from the U.S. to other countries [56] and cross-country collaborations [57], macro level considerations become even more important. While these are beyond the control of the company management, understanding the unique predictors and their degrees of importance that drive IT workers' turnover in different countries can help researchers and practitioners develop more contextually sensitive retention practices and expectations in our increasingly globalized IT world.

The value of information systems, synonymous with IT [58], [59], depends on how successfully users may apply them in their own contexts. The same technologies employed in different contexts have different impacts [60]. This also applies to IT workers: while their technical knowledge may be similar, their attitudes and uses of technologies are conditioned by different cultural, political, and labor market contexts. Extrapolating further, we argue that the dominant U.S.-centric literature on other issues is not equally applicable in all countries of the world. As this study shows, there are limits to applying U.S.-based findings to other countries. Thus, a more context-driven approach in IT research can enrich the literature toward a more global, comprehensive coverage, thereby widening the range of applications globally.

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