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Missing Impact of Ratings on Platform Participation in India: A Call for Research in GREAT Domains

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Abstract:

In this study, we propose that research conducted in Western, educated, industrialized, rich, and democratic (WEIRD) domains does not necessarily generalize to the rest of the world. Growing, rural, eastern, aspirational, transitional (GREAT) domains now account for a significant proportion of world economic output and, thereby, warrant special attention. We submit that a tolerant stance under which scholars investigate GREAT domains with an open mind that allows for theoretical plurality will likely enrich IS theories. To exemplify this stance, we consider how online ratings affect ratee decisions to participate in financial transactions on a digital platform in a GREAT economy. The production and consumption of food affects every strata of society, and, thus, we choose to investigate our research question in the context of platform-enabled food delivery. We applied decision tree induction on a population-level dataset that included restaurants, their features, online ratings, and financial participation decisions from a major food discovery and delivery platform in India. Tree induction makes no distributional assumptions and makes no a priori assumptions on the combinations of factors, which allows one to put forth the most lenient test for uncovering any impact that online ratings have on the decisions that rates make tacitly. After conducting multiple computational experiments, we consistently found that online restaurant ratings did not have a significant bearing on their decision to participate on the food-delivery platform. Our counterintuitive finding serves as an example WEIRD domain logic that does not generalize to a GREAT domain and forms a credible basis for our call for additional research in GREAT domains.

Keywords: Western, Educated, Industrialized, Rich and Democratic (WEIRD) Domains, Growing, Rural, Eastern, Aspirational, Transitional (GREAT) Domains, Digital Platforms, Online Ratings, Food Delivery, India.

Prasanna Karhade and Abhishek Kathuria contributed equally and are co-first authors on this paper.

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1 Introduction

Researchers across various disciplines have increasingly recognized that, while researchers predominantly conduct scientific research in Western, educated, industrialized, rich and democratic (WEIRD) domains (Henrich, Heine, & Norenzayan, 2010a), most people in the world do not live in them (Henrich, Heine, & Norenzayan, 2010b). Though researchers have conducted work in broader international settings (e.g., Ho & Lim, 2018; Venkatesh, Rai, Sykes, & Aljafari, 2016), they have principally conducted a large majority information systems (IS) research in WEIRD domains. This key research choice has strong implications for the theory developed and its potential applicability to the rest of the world. Growing, rural, Eastern, aspirational, and transitional (GREAT) domains, such as India, Indonesia, many nations in South East Asia, South Africa, and Africa, account for a significant proportion of world population and economic output and, thus, warrant special attention in the research literature. Not all research conducted in WEIRD domains pertains to GREAT domains.

Specifically, researchers who conduct most research in WEIRD domains assume that it does or, even worse, should readily generalize to the rest of the world. This assumption takes generalizability for granted and posits that the intended contribution from “replication” research lies, at best, in contextualizing the “correct” theory developed in WEIRD domains by proposing relatively minor incremental changes (e.g., including a new context-sensitive moderator). Rather than assuming that theories developed based on studying WEIRD domains generalize to the world, we submit that, if scholars investigate GREAT domains with an open mind that allows for theoretical plurality, such a tolerant stance will likely enrich IS theories.

In this study, to exemplify this stance, we consider the consequences of user-generated ratings on platform participation in a GREAT domain. In this past decade, we have witnessed rapid transformations in various industries due to the emergence of digital platforms. Many such platforms feature user-generated content and, in particular, online ratings. Consumers do not usually face an explicit cost to produce user-generated content (Duan, Gu, & Whinston, 2008; Hu, Koh, & Reddy, 2014; Pavlou & Dimoka, 2006). Instead, user-generated content affects other consumers’ decision making, and, hence, many platforms encourage consumers to produce and curate user-generated content. Consequently, many platforms such as Yelp and TripAdvisor focus on generating content. A substantive literature examines issues related to user-generated content, its antecedents, and consequences on digital platforms. Researchers have determined ratings, a specific type of aggregated user-generated content, to impact other consumers’ strategic behavior and decision making. While reviews and user interactions capture many nuances (Pavlou & Dimoka, 2006), ratings reflect all these together in a single indicator. In summary, understanding the impact that online ratings have on strategic behavior continues to remain a critical issue.

Researchers have extensively explored whether online ratings matter for financial decisions on digital platforms. In particular, they have examined the effect of three aspects of ratings: valence (e.g., Duan et al., 2008), variance (e.g., Chintagunta, Gopinath, & Venkataraman, 2010) and volume (e.g., Duan et al., 2008). However, after examining the literature, we observed two key gaps.

First, though researchers have examined the effect that ratings have on *raters*’ (i.e., individuals who give ratings) choices (e.g., Pallais, 2014), they have not equally considered how ratings influence *ratees*’ (i.e., individuals who receive ratings) choices (e.g., Tiwana, 2015). Research suggests that ratings influence ratees’ decision making for brand building, customer acquisition, and product development (Dellarocas, 2003). For example, research shows that sellers (ratees) with low ratings are more likely to exit eBay (Cabral & Hortacsu, 2010). However, based a close look at the literature and extensive field evidence, we believe that ratings may not matter for all types of ratees’ strategic decisions.

Second, and more importantly, researchers have principally conducted prior investigations in WEIRD domains. Specifically, we have rather limited knowledge about how online ratings influence ratees’ financial decisions on a platform in a growing, rural, Eastern, aspirational, and transitional (GREAT) economy. Formally, our research design integrates these two gaps by addressing the following research question (RQ):

> **RQ:** How do online ratings affect ratees’ decisions to participate in financial transactions on a digital platform in a GREAT economy?

To answer this research question, we examine *growing* concerns that digital platforms experience via participating in a *growing* economy, leverage data that covers *rural* and urban areas of a major *Eastern* economy, and capture the idiosyncrasies of an *aspirational* economy—with a rapidly growing uppermiddle class with growing disposable incomes—by including a rich set of information attributes to account for the research domain's *transitional* nature.

Food production and consumption affects every strata of society; thus, given food's lasting impact, we choose to investigate our research question in the context of platform-enabled food delivery. To address the research gaps that we outline above, we applied a machine-learning classification technique (i.e., decision tree induction) on a population-level dataset that included restaurants, their features, online ratings, and financial participation decisions from a major food discovery and delivery platform in India. India, one of the most diverse nations in the world, has 22 official languages, dozens of cultures, and a complex gastronomic palate. The country also has over a 100,000 restaurants in the organized sector, which serve diverse, rich, and mature cuisines. The availability of large datasets from India combined with big data analytical techniques have contributed to the emerging computational gastronomy field (e.g., Jain, Rakhi, & Bagler, 2015). Researchers in the strategic management, operations management, and IS literatures have studied India extensively (e.g., Celly, Kathuria, & Subramanian, 2016; Kathuria, Mann, Khuntia, Saldanha, & Kauffman, 2018; Kathuria, Kathuria, & Kathuria, 2018; Kathuria, Khuntia, Karhade, & Ning, 2019; Kathuria & Konsynski, 2012; Kathuria, Porth, Kathuria, & Kohli, 2010; Khuntia, Kathuria, Saldanha, & Konsynski, 2019; Venkatesh, Shaw, Sykes, Wamba, & Macharia, 2017). Our paper represents another step in this direction and towards establishing theoretical plurality's viability by investigating complex phenomena in GREAT domains.

Our initial dataset included nearly 96,000 restaurants across 37 cities in India. After dropping restaurants without ratings, we analyzed how 59,921 restaurants made platform-participation decisions by leveraging decision tree induction. By doing so, we could model ratees' cumulative decision experiences and ascertain ratings' role as the ratees participated in food delivery on the platform (March, 1994). Though researchers have used this induction methodology (Quinlan, 1986, 1990) sparingly in the past (e.g., Pomerol, Brezillon, & Pasquier, 2002; Tessmer, Shaw, & Gentry, 1993; Tsang, Yung, & Li, 2004), we have seen an increase in recent applications due to methodological advancements and the availability of large datasets. Computational experiments through decision tree induction have several advantages, such as a lack of distributional assumptions and the ability to discover underlying patterns in the data and decision-making attributes (Boonstra, 2003; Langley, Mintzberg, Pitcher, Posada, & Saint-Macary, 1995; Markus, Majchrzak, & Gasser, 2002). These advantages benefit our research question and theory development (Karhade, Shaw, & Subramanyam, 2015) due to low rate of false positive predictions (Spangler, May, & Vargas, 1999) and a lack of a priori assumptions regarding antecedent combinations.

We found that ratings on a digital platform do not make up part of the decision-making attributes for the ratees (restaurants) when they decide whether to participate in food delivery on the digital platform. In other words, we found that ratings do not matter to ratees in a GREAT domain (at least for explaining their decisions to participate in financial transactions on a digital platform). In summary, we elaborate on the missing impact that user-generated ratings have on ratees' decisions to participate on a food-delivery platform in India to exemplify a WEIRD domain logic that does not generalize to a GREAT domain. This counterintuitive finding serves as a credible basis for our call for research in GREAT domains. We request researchers to approach GREAT domains with an open mind as theories developed in WEIRD domains may not generalize to the rest of the world, which creates opportunities to develop new theories. Though such new theories may themselves not readily apply to the rest of the world, which includes both WEIRD and other non-WEIRD domains, they may apply to many emerging markets in Asia and Africa and to a stratum of consumers in WEIRD domains and, thus, would enrich our field and collective knowledge about IS phenomena.

This paper proceeds as follows: in Section 2, we review work in related research areas and identifies key gaps. In Section 3, we formulate our model by presenting the tree induction classification methodology, the research context and data, and the model setup. In Section 4, we report heuristics we used to select the best model, our computational experiments, and results and key observations from our investigation. Finally, in Section 5, we summarize our contributions for theory and practice, elaborate on the study's boundaries, and discuss potential future research directions. Finally, in Section 6, we conclude the paper.

2 Background

2.1 Related Research in WEIRD Domains

Related research has established that user-generated online ratings have a strong influence on other users' behaviors. Research has demonstrated that consumers reduce their cognitive effort and resort to simplifying strategies for decision making as a response to two issues: 1) information complexity and abundance and 2) cognitive limitations to processing this information in a limited time (Hu et al., 2014; Karhade & Dong, forthcoming-a; Karhade & Dong, forthcoming-b; Tversky & Kahneman, 1974). Researchers consider information that people can easily align or interpret through numeric values along a standard scale (Hsee, 1996) more accessible and less effortful to process. Thus, consumers use numerical ratings to simplify (reduce) the amount of effort that they expend on making decisions about selecting and purchasing products. Formally, ratings reduce information asymmetry in digital platforms by soliciting and displaying information about transaction quality to market participants. Hence, ratings can improve efficiency and overcome market failure (Pallais, 2014).

Much related literature has examined the effect that ratings' valence (Duan et al., 2008), variance (Chintagunta et al., 2010), and volume (Duan et al., 2008) have on raters' decision-making process with respect to product sales. Some common themes have emerged from this literature. First, ratings matter but not always: researchers have found mixed empirical results (Duan et al., 2008; Lee, Hosanagar, & Tan, 2015). While some studies have found that rating variance and volume has no effect on sales, others have found negative and significant effects (Duan et al., 2008). Second, the nature of the product or service being rated and the nature of the rating system (one-sided versus two-sided ratings) matter: they influence ratings' distribution and consequences. For example, 31 percent of ratings on TripAdvisor and 44 percent on Expedia are five-star ratings as compared to 75 percent on Airbnb (Mayzlin, Dover, & Chevalier, 2014). Also, some researchers have found that ratings have no significant impact how much movies make at the box office (e.g., Duan et al., 2008), whereas others have found positive (e.g., Chintagunta et al., 2010) and even long-term impacts (e.g., Lee et al., 201). On the other hand, several studies have established that ratings have a positive effect on electronic product sales. Third, one needs other review aspects beyond ratings to explain all nuances of raters' decision-making behavior with regards to sales (Pavlou & Dimoka, 2006) because numeric ratings do not fully capture the polarity information in reviews (Ghose & Ipeirotis, 2011). Thus, ratings mostly have an indirect effect on sales rank through sentiments, while sentiments mostly affect sales rank directly (Hu et al., 2014). Finally, the little research that has examined the effect that ratings have on rates has found that ratings matter. Ratees with lower ratings witness drops in sales and more frequent subsequent lower ratings (Cabral & Hortacsu, 2010). Also, low ratings increase the chance that ratees will exit the market (Cabral & Hortacsu, 2010). Considering these broad themes in this research that researchers have conducted in WEIRD domains, we can plausibly conclude that ratings should affect ratees' decision to participate in subsequent financial transactions on a digital platform in a GREAT domain. In summary, while research has clearly established the impact that user-generated online ratings have other users' behavior, we need to further investigate the impact that online ratings have on ratees' behavior.

2.2 Research Design and Linkages of this Study to GREAT Domains

We assert that research findings from WEIRD domains do not necessarily generalize to similar phenomena in GREAT domains. In this research, we investigate the impact that user-generated online ratings have on ratees' behavior in a GREAT domain. As we describe next, our research design ensures strong linkages to the key ideas that drive economic activity in GREAT domains.

2.2.1 Growing

We study a growing economy and digital platforms' growth in it. As more restaurants participate on a food-delivery platform, the platform grows by arguably encouraging more citizens to participate on it. Thus, given that we examine platform participation, we address growth in GREAT domains and, in doing so, investigate growing pains that digital platforms experience in growing economies.

2.2.2 Rural

Given the immense diversity of India, we painstakingly collected a pan-Indian dataset for this study. Since a significant proportion of India remains rural, our research has strong implications for the impact of digital platforms in both urban areas and rural domains. The juxtaposition of the logics driving platform participation in rural versus urban areas is critical to answering our research question, and we formulated a data collection strategy for this research accordingly. Additionally, our tree methodology organizes our findings holistically in one tree, which means we can easily compare these underlying logics across rural and urban domains.

2.2.3 Eastern

Our research design makes a strong link with the Eastern dimension as we collected our data in India. With our empirical context and the data-collection strategy, we could capture the dynamics governing digital platforms' participation in Eastern economies. Eastern philosophies shape both consumers' and restaurants' behavior (e.g., vegetarianism). This empirical context has a strong influence on the drivers and, more importantly, combination of drivers for explaining platform participation.

2.2.4 Aspirational

India has a growing and aspirational population. We capture this aspirational nature along many dimensions via the various information attributes that our data includes. The Indian populace aspires to enjoy digital platforms and home food delivery. The Indian populace also aspires to enjoy Indian, international, and fusion cuisines from all around the world. Large parts of India have traditionally been vegetarian, and many people now aspire to enjoy a protein-rich, meat-based diet. Overall, how an aspirational India feeds itself will have strong implications for this planet.

2.2.5 Transitional

India and its economy have begun to transition. We can see this transition across many dimensions and in the country's entrepreneurial activity. We can see transformations in India in every sector of the economy, such as in the new-age, digital-native business models and the more traditional brick-and-mortar business models that restaurants use. Restaurants in India have traditionally provided home food-delivery services for a long time and have begun to consider migrating to the platform-based food-delivery ecosystem. Furthermore, simultaneous transitions have begun to occur in the country's other economic spheres. For instance, cash payments have always been predominant in India. However, it has begun to transition to various digital financial instruments. Again, due to the various information attributes that we collected, we could systematically capture the transitional nature of our empirical domain and holistically study platform participation in India.

In summary, we need research that integrates multiple dimensions of GREAT domains. Our research design addresses this gap by leveraging induction. As we discuss in Section 3, tree induction suits work in which one focuses on identifying combinations of factors that drive participation across the various dimensions of GREAT domains.

3 Model Formulation

3.1 Machine Learning for Classification

Classification with machine learning (e.g., tree induction) is a data-driven methodology for discovering patterns from data (Quinlan, 1986, 1990). Induction yields easy-to-interpret rules that shed light on tacit decision rationale to make informed inferences about decision making (Boonstra, 2003; March & Shapira, 1987). Trees are accessible to a variety of stakeholders, such as top management executives and policy makers (e.g., Karhade et al., 2015; Langley et al., 1995), as they represent discovered patterns via trees of if-then rules. More often than not, stakeholders can find it difficult to articulate business logic as it tends to be tacit.

Classification via tree induction opens the black box of the tacit business logic and represents interrelationships between various decision attributes and outcomes. Using machine-learning techniques for classification effectively allow one to discover attribute combinations that one may not know ex ante and to compactly represent their cumulative influence on outcomes (Langley et al., 1995; Markus et al., 2002). Trees shine the light on emergent interconnections between decision attributes (i.e., the attributes included in the tree) (Langley et al., 1995; Markus et al., 2002). Thus, trees weed out features that do not informatively explain outcomes. Note that all the information attributes that characterize all decisions serve as inputs to tree induction, and the algorithm identifies only information attributes pertinent to decision making. We refer to these pertinent information attributes that appear in the decision tree as decision attributes to signify their importance.

Moreover, tree induction makes few distributional assumptions about the data, which makes the methodology more generalizable. Overall, trees present an appropriately lenient method to discover the effect that restaurant ratings have on the restaurants' decision to participate online, whether in isolation or in any combination with other information attributes, which one will not likely know ex ante.

Data partitioning represents a key practice associated with using tree induction. In essence, data partitioning and creating non-overlapping training and validation partitions involves demonstrating discovered knowledge's generalizability. The algorithm learns knowledge, represented in the form of trees, from the training partition, and one validates its prediction accuracy on unseen data. In other words, one can consider knowledge that one discovers from training data as generalizable only if it accurately predicts unseen data (from the non-overlapping validation data partition).

A testing mode called n-fold validation, which divides data into n partitions and uses n-1 partitions as the training sample and one partition (or fold) for validation, builds on the partitioning idea. In this study, we use 10-fold validation, a popular testing mode for induction. However, because data scientists over-fit their models and explain noise in their data (as opposed to explaining the underlying relationships of interest), we take necessary precautions and not fall into the over-fitting trap by using data partitioning. We assess the generalizability of the knowledge discovered based on the training data by testing its prediction accuracy on unseen data from the validation data partition.

Table 1. Information Attributes for Participation in Financial Transactions

No.	Information attributes	Values
1	Cost	Low: cost of meal for two persons less than or equal to 300 Indian Rupees (approx. US$4) Medium: cost of meal for two persons between 300 and 1000 Indian Rupees High: cost of meal for two persons greater than or equal to 1000 Indian Rupees (approx. US$14)
2	Cuisines	Low: serves a single cuisine / medium: serves two or three cuisines / high: serves more than three cuisines
3	Vegetarian	No: serves non-vegetarian dishes / yes: serves only vegetarian dishes
4	Indian	No: serves non-Indian cuisine / yes: serves only Indian cuisine
5	Alcohol	No: does not serve alcohol / yes: serves alcohol
6	Offers parking	No: no parking provided / yes: provides paid, free or valet parking services
7	Go-In	No: offers no live entertainment, music, or telecast of live sporting events Yes: offers live entertainment, music or telecasts live sporting events
8	Wi-Fi	No: does not offer free Wi-Fi Internet access / yes: offers free Wi-Fi Internet access
9	Digi-Pay	No: does not accept digital payments / Yes: accepts payments through digital wallets
10	Chain	Low: has unique name Medium: at least one and less than nine other restaurants have a similar name High: nine or more than nine other restaurants have a similar name
11	Metro India	No: located in city other than Bangalore, Chennai, Delhi, Hyderabad, Kolkata, Mumbai, or Pune Yes: located in Bangalore, Chennai, Delhi, Hyderabad, Kolkata, Mumbai, or Pune
12	Ratings	Low: rating less than 3 out of 5 Medium: rating greater than or equal to 3 and less than 4 out of 5 High: rating greater than or equal to 4 out of 5

3.2 Induction Model Formulation

After data partitioning, two steps define classification via machine learning. First, one uses the C4.5 to grow the tree based on training data (Quinlan, 1986, 1990). Second, one prunes the tree that one grows in the first step by validating it with unseen data from the validation partition. By employing high levels of pruning, we can discover the data's tacit structure and demonstrate the discovered knowledge's robustness. We used the Weka software application, an open-source platform, to partition data and grow and prune trees (Hall et al., 2009). The C4.5 algorithm relies on the concept of purity and uses informative attributes to recursively partition the training data to reduce impurity in terminal nodes. We chose entropy as the impurity measure as one can easily interpret it for a two-class decision problem. The basis for entropy reduction lies in the mathematical theories of communication (Shannon, Weaver, & Burks, 1951).

Tree induction iteratively groups together observations (i.e., restaurants) such that they resemble each other in not only certain information attributes (information attributes from Table 1) but also their participation in financial transaction outcomes. We used two inputs for the tree induction: 1) restaurants described using all information attributes (see Table 1), and 2) restaurants' decisions to participate in financial transactions. We used tree induction to discover tacit combinations of information attributes associated with similar final outcomes (i.e., similar decisions regarding financial transaction participation) (Quinlan, 1986). Trees retain only the most pertinent decision attributes for explaining decisions and organize decision attributes in a context-dependent manner (Quinlan, 1990). If one uses a decision tree's prediction accuracy as the sole criterion when choosing the best representative tree (among alternative models), one could obtain misleading results and fall into the over-fitting trap. Consistent with prior research (e.g., Kathuria, Karhade, & Konsynski, 2020), we avoid relying too much on prediction accuracy by considering two additional heuristics: 1) the discovered knowledge's communicability and 2) its consistency. In summary, the discovered knowledge's 1) prediction accuracy, 2) communicability, and 3) stability guide what tree one chooses as the best representative one.

Trees discovered by induction do not reflect the exact rules or "scripts" that decision makers use but rather represent credible approximations of the decision rationale (Boonstra, 2003). Rather than the correlations between attributes, induction relies on the amount of information a particular attribute conveys about the decision outcome.

3.3 Research Context and Data

India represents an apt setting to examine our research question in a GREAT domain. A largely agrarian society, India has been one of the fastest growing major economies in Asia and the world during the recent decade (Kathuria et al., 2018). As such, the country now contains a large group of consumers who aspire to buy Western products and services (Celly et al. 2016), which has resulted in a transitional economy (Khuntia et al., 2019). Specifically, as our research context, we used a large, comprehensive restaurant discovery and food-delivery digital platform based in India. This platform had a pan-India presence and operated for more than three years in all large cities in India. This platform comprised two distinct elements: a website to review and rate restaurants and a separate online marketplace for ordering food. The website listed all registered restaurants in India regardless of whether they participated in financial transactions in the marketplace (food delivery through the platform). Thus, all restaurants received ratings (subject to a few conditions that we discuss at the end of this section). This practice effectively addresses concerns stemming from sample selection bias as we could observe rates regardless of whether they participated in the marketplace or not. The platform did not levy fees from customers and, thus, did not cross-subsidize restaurant participation in financial transactions. Therefore, the underlying fee and payment structure's dynamics did not influence restaurants' financial transaction participation choices. Finally, in our setting, multi-homing costs were low and a restaurant could choose to affiliate with any number of digital platforms. Research suggests that winner-take-all outcomes will not likely arise in such domains (Hagiu, 2009).

Our dataset contained a population sample of 95,735 restaurants that served 135 different cuisines and resided in 37 cities of India. Our sample contained restaurants across India if the digital platform listed them. Any consumer could list a restaurant on the website, and listed restaurants could garner reviews and ratings from other consumers. Restaurant owners needed claim the listing if they wanted to provide verified details such as an official menu, contact information, and opening hours. Restaurant owners also needed to make a strategic choice about whether they wanted to participate in financial transactions through the marketplace. Mere listing did not imply participation.

Choosing to participate in financial transactions on the marketplace represented a nontrivial decision that could have different outcomes. Participating in financial transactions on the marketplace could increase demand for the restaurant's products among customers who used the marketplace. Thus, restaurants could increase their sales. However, this decision carries an increased risk that the restaurant could possibly not be able to fulfill demand arising from the online marketplace, which would adversely impact its rating and its sales (National Restaurant Association of India, 2016). Specifically, the risk arose due to three main reasons. First, restaurants paid the digital platform a fee inversely proportional to the transaction value as per a multi-tier structure. Second, restaurants could possibly not cope with high spikes and unforeseen growth in demand. Third, adverse reputational affects could accrue owing to a mismatch in service levels at the restaurant and the stakeholders on the platform (e.g., delivery personnel).

3.4 Outcome Variable and Attributes

We investigated an individual restaurant's decision to participate in food delivery through the digital platform and, thus, digitize a certain proportion of its business transactions. We coded the outcome variable, participation (mean = 0.62, SD = 0.49), as "yes" if the restaurant participated in the food delivery and as "no" if it did not. Next, we describe the attributes we included in our theory.

The first key attribute we included was how much its food costs according to a meal for two people (mean = 581.75, SD = 523.82). This cost reflects a restaurant's strategic positioning (e.g., cost leadership (Porter 1985; Porter & Millar, 1985). Specifically, we coded this variable as "high" for a restaurant that offered a meal for two persons for 1000 Indian Rupees (INR) (approximately US$14) and above, "medium" for a restaurant that offered a meal for two people that cost between 300 and 1000 INR, and "low" for a restaurant that offered a meal for two people that cost less than or equal to 300 INR (approximately US$4).

We coded number of cuisines (mean = 2.28, SD = 1.19) as "low" if a restaurant offered a single cuisine, medium if it offered two or three cuisines, and high if it offered more than three cuisines. We captured vegetarian-only restaurants with a dummy variable called vegetarian (mean = 0.28, SD = 0.45). We coded this variable as "yes" for vegetarian-only restaurants and as "no" otherwise. Similarly, we captured whether a restaurant provided only Indian food (vs. world cuisines) using a dummy variable called only Indian (mean = 0.14, SD = 0.35). We coded this variable as "yes" if a restaurant served only Indian food and "no" otherwise.

We captured whether a restaurant served alcohol using a dummy variable called alcohol (mean = 0.14, SD = 0.35). We coded this variable as "yes" if a restaurant served alcohol and as "no" otherwise). We captured whether restaurant provided any form of parking services using a dummy called offers parking (mean = 0.10, SD = 0.29). We coded this variable as "yes" if a restaurant provided any (paid, free, or valet) parking services and no otherwise. Restaurants can provide additional services to encourage customers to specifically go in and visit the restaurant. Such features include live entertainment, music, telecast of live sporting events, and so on. We captured whether a restaurant provided any features that might encourage customers to dine in (as opposed to ordering in) using a dummy called go-in (mean = 0.08, SD = 0.28). We coded this variable as "yes"" if a restaurant provided additional features such as live entertainment, music, or telecasts live sporting events and as "no" otherwise.

Two attributes captured a restaurant's technology readiness. First, we captured whether restaurants accepted electronic payments using a dummy variable called digi-pay (mean = 0.09, SD = 0.28). We coded this variable as "yes" if a restaurant accepted payments digitally through wallets and as "no" otherwise. Second, we captured whether a restaurant provided free Wi-Fi Internet access to its customers using a dummy variable called Wi-Fi (mean = 0.13, SD = 0.33;). We coded this variable as "yes" if a restaurant provided its customers with free Wi-Fi Internet access and as "no" otherwise.

Another key institutional attribute that we captured corresponds to whether a restaurant was part of a group of restaurants with the same name. These restaurants may be part of a chain or might share a common name that reflects a well-established identity (Hannan & Freeman, 1977). Institutional norms will likely occur across restaurants that belong to the same chain or group (Scott, 1987); hence, such restaurants will have a similar their propensity to participate in financial transaction on the platform. Thus, we captured this attribute by coding the chain variable as "high" if nine or more other restaurants had the same name as a focal restaurant, "medium" if at least one other restaurant (but no more than nine) had the same name as a focal restaurant, and "low" if the restaurant had a unique name.

We also captured a key environmental attribute corresponding to India's unique context. Restaurants located in metropolitan cities in India (e.g., Mumbai, Delhi, Chennai, Kolkata Pune, Hyderabad, and Bangalore) will likely systematically differ in their propensity to participate in financial transactions on digital platforms compared to restaurants in the rest of semi-urban and rural India. Thus, we captured these differences using an attribute called metro India. We coded this variable as "yes" if a restaurant operated in the top seven metros Mumbai, Delhi, Chennai, Kolkata, Pune, Hyderabad, and Bangalore and as "no" otherwise.

Finally, we captured the focal variable, a restaurant's online rating (mean = 3.26, SD = 0.44). A restaurant's online rating represents its reputation or social capital in the digital world. A restaurant's offline reputation migrates to the digital platform as more and more customers review and rate the restaurant. Overall, since the final online rating reflects the cumulative information that the reviews contain, we included only the overall online rating in our analysis. This website recorded a restaurant's rating on a five-point scale. We transformed ratings from their numeric value to three categories (i.e., high, medium, and low) as follows: we coded a restaurant as high when it had a rating more than or equal to 4 4, as medium when it had a rating more than or equal to 3 but less than 4, and as low when its rating was less than 3.

3.5 Missing Ratings

Certain restaurants did not have ratings, which we excluded from our analysis. In all, 35,815 (37%) restaurants had missing ratings. One can typically find such inactivity when studying digital platforms and online marketplaces. Due to network effects-based incentives, such providers wish to display large number of participants to the other side of the market. Many platforms do not delete inactive participants or reveal that a restaurant has ceased to participate in financial transactions. We observed that a large number of the missing ratings in our population belonged to restaurants that went of business. Newly opened restaurants do not have a rating for the first three months due to website regulations. Finally, restaurants that have not accumulated a significant number of reviews also do not have a rating.

We conducted detailed ex post analysis on this subsample. We found that 12,679 of the restaurants without ratings operated outside the seven metros, which was not proportional to the total number of restaurants outside the metros. This finding implies that, in smaller cities, people did not use the platform for reviews. A disproportionate number of restaurants (20,033) had low prices; these restaurants plausibly did not have enough reviews because their customers arguably were not technology savvy. Finally, nearly half the restaurants (17,296) participated in financial transactions through the marketplace. Overall, we can infer that half the restaurants without ratings did not have enough reviews, whereas the other half were either closed or newly opened. In summary, we excluded restaurants without ratings from our main analyses.

3.6 Model Setup

To ensure that we comprehensively discovered decision rationale, we repeated a process in which we drew mutually exclusive training and testing subsamples. We describe a tree induction iteration next. In each iteration, we draw random and mutually exclusive subsamples of restaurants from the original data: one set called the training set from which the C4.5 induction algorithm discovered the tacit decision rationale (Quinlan, 1986), and another disjoint set of initiatives called the testing set that we used to test the predictive accuracy of this discovered rationale. We used 10-fold validation where we divided the full sample into 10 partitions: we used nine to build the tree and the last one for validation. The tree induction algorithm assesses the prediction accuracy of the tree discovered from training set by predicting decisions for restaurants from unseen data using the validation set.

4 Computational Experiments

4.1 Attribute Selection and Heuristics for Identifying Best Representative Model

We derived multiple approximations of the tacit rationale by repeating the 10-fold validation process at varying pruning levels. Induction requires these experiments to ensure that researchers have multiple approximations of the underlying decision process. We relied on three heuristics to select the best representative, a credible approximation, of the tacit decision process.

1) High predictive accuracy: we tested the prediction accuracy of trees that we induced on training data on mutually disjoint validation data. This heuristic represented a goodness of fit for the tree that we induced on the training data in terms of predicting decisions from unseen data.

2) High parsimony: we expected the induced tree to parsimoniously approximate the decision rationale so that it could serve as an effective decision- and policy-making aid.

3) High reliability: since we drew training samples to induce trees and tested the predictive accuracy of the induced trees on the validation samples several times, we could assess the discovered knowledge's robustness. All trees that we induced on the data contained the same top-most attribute across these multiple iterations and, thus, represent robust findings. Thus, we can claim that the trees that we present here credibly approximate the restaurants' tacit decision process for participation in financial transactions on the platform.

The trees we present here approximate the decision process and, thus, do not represent exact rules or "a scripted rulebook" that decision makers use. Since we employed three heuristics (high prediction accuracy, parsimony, and reliability) to choose a best representative tree, the selected tree credibly approximates the interrelationships between attributes for explaining platform participation.

All twelve information attributes characterizing restaurants (see Table 1) in conjunction with the final financial transaction participation decision served as inputs to induction. We included all information attributes that we deemed informative for explaining participation decisions in the trees as decision attributes, and the induction algorithm excluded all the non-informative attributes from the tree. The top-most attribute in the tree represents the most informative decision attribute. Attributes' importance decreases as we move away from the top of the tree to its leaves as trees organize attributes in a context-dependent manner (Quinlan, 1990).

Table 2. Computational Experiments

No.	Degree of pruning	Min instances on the leaves	Number of leaves	Top two levels of decision attributes	Prediction error	Ratings
1	Low	100	25	1: Urban India 2: digi-pay, cost	31.80%	Not in the tree
2	Low	200	21	1: Urban India 2: Digi-pay, cost	31.77%	Not in the tree
3	Low	500	24	1: Urban India 2: digi-pay, cost	31.91%	Lowest in the tree
4	Medium	100	28	1: Urban India 2: digi-pay, cost	27.72%	Not in the tree
5	Medium	200	21	1: Urban India 2: digi-pay, cost	31.75%	Not in the tree
6	Medium	500	24	1: Urban India 2: Digi-pay, cost	28.12%	Lowest in the tree
7	High	100	21	1: Urban India 2: Digi-pay, cost	31.83%	Not in the tree
8	High	200	21	1: Urban India 2: Digi-pay, cost	31.83%	Not in the tree
9	High	500	19	1: Urban India 2: Digi-pay, cost	32.00%	Not in the tree
10	Aggressive	100	19	1: Urban India 2: Digi-pay, cost	31.97%	Not in the tree
11	Aggressive	200	20	1: Urban India 2: Digi-pay, cost	32.05%	Not in the tree
12	Aggressive	500	20	1: Urban India 2: Digi-pay, cost	32.04%	Not in the tree

4.2 Setup of Computational Experiments

We generated alternative models by changing the degree of pruning and the minimum number of instances (i.e., restaurants) on the trees. We used all 12 attributes to model platform-participation decisions. Across all our computational experiments, urban India consistently appeared as the top-most classification attribute and the ratings attribute did not appear at all.

Given our counterintuitive findings and ratings' importance in the extant literature, we explored additional combinations of the degree of pruning and the minimum number of instances (i.e., restaurants) on the leaves (see Table 2 above). In some scenarios, we could induce trees that included ratings as a predictor. In all such instances, ratings consistently appeared as the least important predictor. These findings represent strong evidence to suggest that, in this case, ratings did not influence ratees' decision to financially participate in this GREAT domain.

5 Results and Discussion

5.1 Key Finding

Counter-intuitively, we found that the decision tree did not include ratings (see Appendix A). This finding suggests that ratings do not substantively influence ratees to participate in financial transactions on the platform. Based on this finding, we qualify ratings' explanatory power as follows: though ratings represent a key factor that guides individual consumers on digital platforms and, in some cases, may also guide ratees' behaviors, user-generated ratings do not explain ratees' financial transaction participation decisions on a food-delivery platform in India. Overall, our finding that ratings had no significant effect and the evidence that shows their strong effect in WEIRD domains lends credence to our claim that findings from WEIRD domains do not readily translate to GREAT domains.

5.2 Other Observations Linked to Specific Branches in the Decision Tree

We now elaborate our other findings in the different cost ranges. Taken together, these observations suggest systematic differences across rural and metro India and, thus, raise the possibility of theoretical plurality in Bharat versus India.

5.2.1 Observation 1: Examining the Metro India Branch

In metro India, high-cost, standalone, non-chain restaurants chose not to conduct financial transactions on the digital platform. Additionally, low-end non-vegetarian restaurants in metro India tended to participate on the digital platform to conduct business transactions.

5.2.2 Observation 2: Examining Restaurants in the Medium-cost Range

In the medium-cost range, we discovered contrary findings across metro India and the rest of India. In metro India, a large majority of restaurants in the medium-cost range conducted financial transactions on the digital platform. On the other hand, in the rest of India, we found that almost half of the restaurants in the medium-cost range did not conduct transactions on the digital platform.

5.2.3 Observation 3: Examining Restaurants in the Low-cost Range

In the low-cost range, we discovered contrary findings across metro India and the rest of India. In the rest of India, we found that most low-cost restaurants did not conduct transactions on the digital platform. On the other hand, a larger proportion of restaurants in metro India conducted transactions on the digital platform.

5.2.4 Observation 4: Examining the Impact of Digital Payments

Most restaurants that offered digital payments in both metro India and the rest of India conducted transactions on the digital platform. On the contrary, when restaurants offered Wi-Fi access to their customers, they tended not to conduct transactions on the digital platform.

5.2.5 Other Observations: Restaurants Serving Alcohol

Across the board, restaurants that served alcohol tended not to digitize their financial transactions on digital platforms. In the rest of India, we discovered a weaker pattern explaining why restaurants conducted transactions on digital platforms and a stronger pattern explaining why restaurants did not conduct financial transactions on the digital platform. On the contrary, we discovered a larger proportion of restaurants conducted transactions on digital platforms in metro India. In the rest of India, restaurants that served an international cuisine tended to broaden their reach by conducting financial transactions on digital platforms.

5.3 Discussion

In this paper, we submit that not all research conducted in WEIRD domains necessarily pertains to GREAT domains. As an example, we studied how ratings affect ratees' strategic choices and decision making on a digital platform in a GREAT domain. While researchers have extensively examined the effect that ratings have on raters' (e.g., consumers) behavior, to our knowledge, there have been few attempts in the literature to address the ratees' perspective. Our analyses answer an important question in a specific context: do online ratings on a platform affect ratees' (restaurants) decision to participate in financial transactions on the platform? To address this gap, we applied a machine-learning classification technique on a population-level dataset that included restaurants, features, and ratings from a major food platform in India.

We used the C4.5 decision tree algorithm to initialize a solution on training data. We then conducted a series of computational experiments wherein we used unseen data to repeatedly apply a 10-fold validation process at varying levels of pruning. With this approach, while one avoids the common over-fitting trap, decision trees themselves make false positive predictions at a low rate. Thus, due to our empirical choices, we present our key findings with high confidence. We show that ratings do not matter to ratees in a GREAT domain. Specifically, ratings on a digital platform do not form part of ratees' (restaurants) decision-making attributes when they decide whether to participate in financial transactions on the platform. This counterintuitive finding supports our call for research in GREAT domains.

We can speculate many reasons why online ratings might not have influenced ratees' decisions to participate on the platform. The website expressed online ratings only in English, and not all of India uniformly speaks English. Thus, this factor could present a distorted picture. Thus, the digital platform tapped only into people who could afford to own smartphones in India and speak English. Furthermore, individuals in Eastern collectivistic economies will likely rate restaurants differently. Common parlance in Indian cultures does not commonly include one-star or five-star rating. In summary, many different forces affect how ratings influence ratees' behavior in GREAT as compared to WEIRD domains.

Our findings have implications for both practice and research. In line with our research question, we develop practice implications for two key stakeholders: platform designers and ratees. First, while researchers have demonstrated ratings to have a significant impact on raters' strategic behavior, it may not be a salient feature in ratees' decision-making processes in GREAT domains. Thus, designers of digital platforms and online marketplaces—specifically designers who originate from WEIRD domains—should realize that features other than ratings form the organizing principles for increasing participation in financial transactions and, thus, growing their installed rate base. Platform designers should take actions to contextualize their platforms to the target domain by making appropriate changes to user interfaces and business processes.

Second, follow-up analyses offer a nuanced view into ratees' decision-making process regarding participation in financial transactions on digital platforms. Thus, restaurant managers in GREAT domains can use our findings to identify competing restaurants that participate on digital platforms and, hence, benefit from an extended catchment area of consumers but pay high transaction fees to the platforms. These restaurant managers should take competitive actions to leverage this information such as making appropriate changes to the variety, price, and serving size of their menu items.

Our practice implications may also extend to other domains with non-exclusive digital platforms. Our findings indicate that managers in GREAT domains should not merely imitate management theory and practice developed in WEIRD domains. Instead, they should be receptive to the notion that there may be another "right" way to do things.

For research related to ratings specifically, our work makes a key theoretical contribution. Ratings represent a critical decision feature when one studies the decisions that participants on digital platforms and online marketplaces make. Our study shows that ratings do not matter for specific stakeholders (ratees), for specific decisions (participating in financial transactions), under specific domains (growing market in a non-Western economy). Researchers should and need to test similar ideas in other domains and on other strategic choices that ratees make, such as change in engagement level, scope of participation, and platform abandonment. Methodologically, the C4.5 decision tree algorithm, which has low rate of false positives, that we used serves as a sample context where researchers can apply machine-learning classification techniques (Spangler et al., 1999). Finally, at a more abstract level, our work suggests that scholars should question the extent to which prior research conducted in WEIRD domains applies to GREAT domains.

Despite providing valuable insights, one needs to interpret our results in the study's boundaries. First, we focused on only one specific decision that ratees make (participating in financial transactions). Realistically, ratees might make various strategic decisions about increasing or reducing their exposure to a digital platform. As we note above, researchers could extend our work by examining other types of strategic choices as ratings' consequences. Second, our results may also have limited generalizability to other contexts (digital platforms and online marketplaces). Thus, researchers could also meaningfully extend this research by examining this phenomenon under other contexts. Finally, due to our data's cross-sectional nature, we could not examine temporal variations through our analysis. Perhaps ratings do matter to ratees when deciding to participate financial on a digital platform a nascent stage in its lifecycle or when it has established a monopoly. Future research could examine this interesting topic. Most importantly, readers should note that we have only examined a single case and found that a result that one would expect in WEIRD domains does not hold in a GREAT context. We did not test or claim this idea's universality. We merely submit that scholars should recognize this possibility.

6 Conclusion

Western, educated, industrialized, rich, and developed (WEIRD) domains (Henrich et al., 2010a) serve as the environment in which researchers theorize and empirically validate most IS research, which has strong implications for the nature of theory developed and its applicability, or lack of, to the rest of the world. In this paper, we submit that growing, rural, Eastern, aspirational, and transitional (GREAT) domains, which account for a large proportion of the world's population and economic output, warrant special attention. We submit that the five properties (i.e., growing, rural, Eastern, aspirational, and transitional) of GREAT domains together constitute a singular combination that results in phenomena that warrant investigation beyond the results that research in WEIRD domains has found. Thus, we suggest that not all research that researchers conduct in WEIRD domains necessarily applies to GREAT domains. As an exemplar, we demonstrate a finding in a GREAT domain that is counter-intuitive to the logic that researchers have derived from prior research in WEIRD domains; that is, that ratings on a digital platform do not make up part of ratees' decision-making attributes when they decide whether to participate in financial transactions on the platform. Accordingly, we submit that, if scholars approach these domains with an open mind, which allows for theoretical plurality, such a stance will likely further enrich IS theories. Accordingly, we call for research in GREAT domains.

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Appendix A

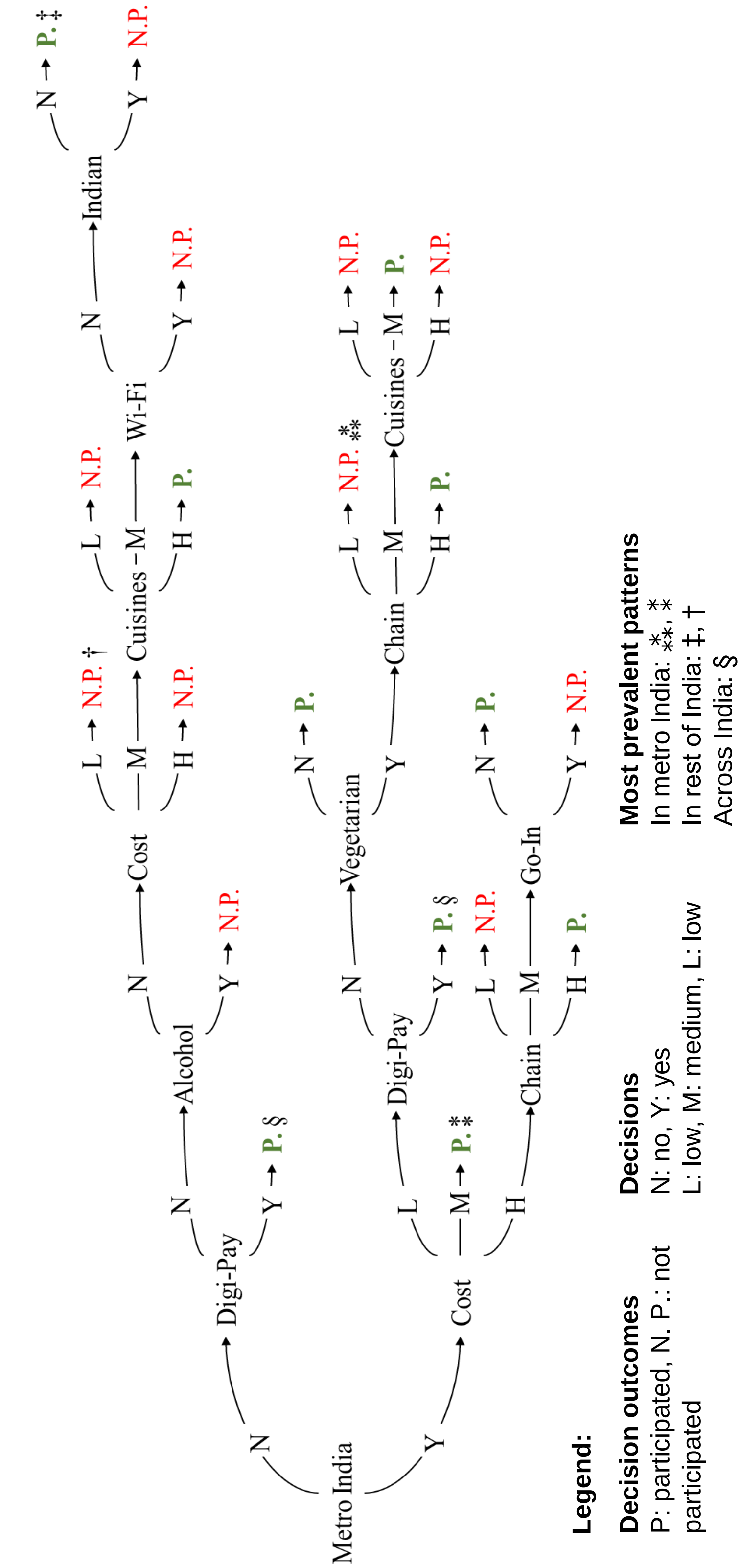

Figure A1. Best Representative Decision Tree

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