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Addressing Perceived Resistance to Biometric Security Systems in Airports:

Exploration With a General Bayesian Network-Based Decision Support System

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ABSTRACT

Ensuring robust security is paramount in the era of global air travel. As airports and other organizations increasingly deploy biometric security systems, end-user resistance poses significant challenges for managers striving to balance security, efficiency, and acceptance. This study develops an interpretable DSS to manage such resistance, utilizing a GBN derived from 339 passenger surveys regarding airport biometric e-gates. The GBN models how perceived risks, compatibility, and trialability shape three distinct resistance outcomes. Building on this model, the authors conduct simulation-based "what-if" analyses across three intervention scenarios to examine how specific design and policy choices can mitigate resistance. An expert evaluation by airport security managers indicates that the DSS's recommendations are realistic and offer improvements over current heuristic strategies. While live field deployment remains a subject for future research, the proposed framework offers a reusable blueprint for DSS design in other biometric and AI-enabled security applications.

KEYWORDS

Biometric Security Systems, User Resistance, General Bayesian Network, Decision Support Systems, What-if Analysis, Airport Security

INTRODUCTION

In most enterprises, technology management and its associated decision-making processes have traditionally been the domain of senior staff and board members. However, in today's competitive global market, relying solely on intuition or hierarchical decision making is no longer feasible. As data analytical models, including machine learning, have become practical, the adoption of model-based, auditable decision processes has become essential. Such a logical framework is referred to as a decision support system (DSS), an information system designed to support interactive decision making for various purposes (Gupta et al., 2007), including technology management. Modern DSS deployments increasingly incorporate machine learning with explainability features and scenario-based evaluations to enable managerial "what-if" reasoning.

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DSSes also serve as valuable tools in the field of innovation studies, as they help formulate appropriate strategies for introducing new technologies to the market. By doing so, they increase the likelihood of successful consumer adoption and reduce the risk of failure (Verleye & De Marez, 2005). In some instances, a DSS can replicate the cognitive process a user undergoes when selecting a new product or service. Much like users, DSSes can be trained to evaluate whether to accept or decline an innovation. Recent evidence in biometric and authentication contexts suggests that adoption hinges on perceived risk, controllability, and trial-like exposure—factors that a DSS can surface and manipulate via scenario analysis (Wang, 2021; Yang et al., 2024; Yu et al., 2024). Typically, users who perceive benefits from an innovation promote its diffusion within the service ecosystem. Yet, adoption tells only half the story; resistance operates through its own distinct determinants and requires explicit modeling.

Innovation resistance theory (IRT) frames resistance not merely as the absence of adoption but as a proactive, autonomous response stemming from specific barriers: (a) usage issues like complexity and incompatibility, (b) value concerns such as limited relative advantage, (c) risks (functional, physical, social, and temporal), and (d) tradition or image factors (Ram, 1987; Ram & Sheth, 1989; Sheth, 1981). This perspective underscores that users may postpone, reject, or oppose innovations for reasons unrelated to diffusion speed or personal "innovativeness," necessitating the direct modeling of resistance rather than inferring it from adoption rates.

IRT complements acceptance models like the technology acceptance model (TAM) and unified theory of acceptance and use of technology (UTAUT), which connect beliefs to intentions and actual use (Davis, 1989; Venkatesh et al., 2003). Central to these models are perceived usefulness (or performance expectancy) and perceived ease of use (or effort expectancy), which map directly onto IRT barriers. For example, functional, physical, social, and temporal risks erode perceived usefulness and heighten perceived effort; compatibility strengthens both expectancies; and trialability lowers uncertainty via low-stakes and reversible trials, boosting overall expectancy beliefs. Studies in biometric and authentication domains confirm these linkages, positioning risk, controllability, and trial experiences as pivotal determinants of acceptance (Wang, 2021; Yu et al., 2024).

Consumers encounter various risks when engaging with innovative technologies due to inherent uncertainties (Martinko et al., 1996; Song et al., 2013). These include temporal risk (wasting time), social risk (negative impressions on others), physical risk (potential bodily harm), and functional risk (performance failures) (Garner, 1986; Kaplan et al., 1974; Ko et al., 2004; Shimp & Bearden, 1982; Song et al., 2013; Stone & Grønhaug, 1993). User traits further shape resistance: openness to innovation, the tendency to seek novelty (Rogers & Shoemaker, 1971), promotes adoption (Manning et al., 1995), while independent decision making, a preference for autonomous choices, eases resistance during the adoption process (Midgley & Dowling, 1978; Song et al., 2013; van Rijnsoever & Oppewal, 2011). Propagation mechanisms also play a role; mass media and digital channels (e.g., search engine marketing (SEM) and social network service (SNS)) reduce resistance by fostering familiarity and countering negative perceptions (Fain & Roberts, 1997; Laukkanen & Kiviniemi, 2010; Rogers, 2003).

Resistance manifests in varied forms, ranging from postponement (Song et al., 2013; Szmigin & Foxall, 1998) to rejection (Rogers, 2003; Song et al., 2013) and active opposition (Kleijnen et al., 2009). Prior research has largely overlooked the segmentation of consumers by resistance intensity (Kleijnen et al., 2009; Song et al., 2013), yet diverse settings like airports require this nuance to address heterogeneous passengers effectively. Unaddressed resistance can delay adoption, hinder propagation, and lead to market failures, as seen in cases like the Woolworth's mousetrap (Ram, 1987; Ram & Sheth, 1989; Sharma, 2015). Importantly, acceptance and resistance are not mutually exclusive; resistance is an inevitable phase in the adoption process that, if unanalyzed, risks major investments and can have lasting negative consequences (Han et al., 2006; Kuisma et al., 2007; Ram, 1987).

Against this backdrop, our DSS operationalized IRT barriers and TAM/UTAUT antecedents using observed factors—functional, physical, social, and temporal risks, compatibility, and trialability. We employed a general Bayesian network (GBN) to estimate how interventions on these levers alter the