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PAPER

User Acceptance of a Research Ethics Management Platform: An Extended Technology Acceptance Model Study in Higher Education

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ABSTRACT

Universities increasingly mediate research ethics review through web-based platforms, but deployment alone does not guarantee acceptance across the heterogeneous roles involved, and technology acceptance model (TAM) studies rarely combine institutional trust (IT), workload, and communication quality in governance workflows. This study extends TAM with IT, perceived workload reduction (PW), and communication channel quality (CCQ) alongside perceived usefulness (PU) and perceived ease of use (PEOU) as antecedents of behavioral intention (BI), with user satisfaction (US) as the outcome. It was applied to a Research Ethics Committee Management System at a private university in Peru (UCH)—reachable from smartphone, tablet, laptop, and desktop browsers, although device-specific acceptance is not modeled—and estimated by partial least squares structural equation modeling (PLS-SEM) with bootstrapping (5,000 resamples) on 120 responses from two exposure conditions: 63 from real institutional use and 57 from a controlled 45-minute demonstration. Invariance between conditions was not established, so conclusions on real use rest on the 63-respondent analysis, where five paths are supported under the confidence-interval rule applied throughout: PEOU → PU ($\beta = 0.465$), PW → BI ($\beta = 0.180$), CCQ → BI ($\beta = 0.290$), PU → US ($\beta = 0.318$), and BI → US ($\beta = 0.452$); the other three are inconclusive at this sample size. The pooled 120-respondent model, exploratory because it merges both conditions, supports six of the eight paths, leaves PEOU → BI inconclusive, and does not support PW → BI, with $R^2 = 0.439$ (BI) and $R^2 = 0.442$ (US). A secondary analysis by reported access device found no construct-level difference except a small, borderline one in PU, with invariance holding for six of seven constructs; it is not a controlled device comparison. Communication channel quality (CCQ) therefore merits attention alongside the traditional utility constructs, whereas IT → BI holds only in the pooled exploratory model and remains inconclusive under real use.

KEYWORDS

technology acceptance model (TAM), partial least squares structural equation modeling (PLS-SEM), institutional trust (IT), research ethics management, higher education, research governance platforms

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1 INTRODUCTION

Institutional research governance—the set of administrative and evaluative processes by which universities review, approve, and monitor research involving human subjects—has traditionally relied on paper-based or email-mediated workflows that are slow, difficult to audit, and poorly adapted to how contemporary researchers and students actually work [1]. Over the last five years, universities across Latin America and other developing regions have progressively replaced these manual procedures with web-based platforms that centralize document submission, evaluator assignment, rubric-based scoring, and applicant–secretariat communication into a single interactive system [2], [3], [4].

Deploying such a platform does not by itself guarantee that the researchers, evaluators, secretariat staff, and coordinators who must use it will accept, trust, and continue to use it. Prior technology-acceptance research on institutional and e-government platforms has repeatedly shown that perceived usefulness (PU) and ease of use, while necessary, are insufficient predictors of sustained adoption when the system handles sensitive institutional records and mediates authority relationships between applicants and evaluators [2], [5], [6]. In such contexts, constructs external to the classical Technology Acceptance Model (TAM)—particularly institutional trust (IT), the perceived reduction of administrative workload, and the quality of the platform's embedded communication channel—have been shown to meaningfully shape behavioral intention (BI) and downstream satisfaction [1], [3], [7].

A specific gap remains in the empirical literature: most extended-TAM studies of institutional systems either focus on a single, homogeneous user population (e.g., students in a learning-management system [8]) or on citizen-facing e-government services with a single role [2]. Multi-role institutional workflow systems—where researchers, evaluators, and administrators interact with functionally different views of the same platform—have received little empirical attention, despite being common in Current Research Information Systems (CRIS) and research governance contexts [9], [10]. Few studies simultaneously model IT, workload perception, and communication-channel quality as parallel antecedents of BI within a single partial least squares structural equation modeling (PLS-SEM) specification.

This study addresses this gap by proposing and empirically validating an extended TAM for a real, in-production Research Ethics Committee Management System deployed at a private Peruvian university (Universidad de Ciencias y Humanidades, UCH). The main contributions of this paper are:

- An extended TAM that incorporates IT, perceived workload reduction (PW), and CCQ as parallel antecedents of BI, alongside the classical PU and perceived ease of use (PEOU) constructs, with user satisfaction (US) as a downstream outcome.
- An empirical validation of this model using PLS-SEM on 120 responses, with full measurement-model assessment (item-level loadings with bootstrap confidence intervals, reliability, convergent validity, Fornell–Larcker and HTMT discriminant validity with bootstrap intervals, and collinearity diagnostics) and structural-model testing (bootstrapped path significance, effect sizes, predictive relevance, and an a-priori power analysis).
- A sensitivity analysis that separates the 63 respondents who used the platform in real institutional activity from the 57 who experienced it through a controlled demonstration and that treats the real-use subsample as the basis for any statement about acceptance under institutional use, because measurement invariance between the two exposure conditions was not established.

- A discussion, stated in language appropriate to a cross-sectional observational design, of which acceptance-related associations institutions may want to attend to when developing or improving research-governance platforms, and of which structural paths are and are not empirically supported under real institutional use.

The remainder of this paper is organized as follows. The Related Work section reviews extended TAM/Unified Theory of Acceptance and Use of Technology (UTAUT) models, IT in technology acceptance, and PLS-SEM methodology. The System Context section describes the platform under study. The Conceptual Model and Hypotheses section presents the structural model. The Participants and Procedure and Measures sections describe the sample, procedure, and instrument. The Data Analysis and Results section reports the measurement- and structural-model findings. The Discussion and Conclusion section interprets the findings and their limitations.

2 RELATED WORK

2.1 Extended TAM and UTAUT models in institutional contexts

The TAM, originally formulated by Davis to explain information-technology adoption through PU and PEOU [6], remains the most widely applied theoretical lens for studying institutional-system adoption, and the UTAUT extended it with performance expectancy, effort expectancy, social influence, and facilitating conditions to account for organizational and mandatory-use settings [11]. Subsequent systematic reviews of UTAUT2 confirm that most extensions add context-specific constructs rather than replacing the original core, a pattern this study follows by retaining PU and PEOU as the structural core while adding three institution-specific constructs [1].

Several recent studies have extended TAM/UTAUT specifically for e-government and mobile-government (m-government) platforms functionally similar to the research-ethics system studied here. Hakeem and Sulphey applied an extended UTAUT model to citizens' use of m-government services in India, incorporating perceived trust and perceived service quality as antecedents of attitude and intention [3]. Jou et al. examined the accessibility determinants of a mobile government application in the Philippines, highlighting device- and service-diversity factors that shape citizen engagement with mobile-first public platforms [4]. Similarly, Mensah and Khan modified UTAUT to explain mobile banking adoption in China by adding perceived financial cost, awareness, and government regulation as external constructs, reinforcing the broader pattern that institutional or regulatory factors substantially alter the classical TAM/UTAUT path structure when the platform being evaluated is not a purely consumer product [7]. Within the education sector specifically, Elmunsyah et al. applied a modified DeLone and McLean information-systems success model conceptually adjacent to TAM to a learning management system and found that system and information quality remained strong predictors of US even after accounting for use and net benefits, a finding structurally analogous to the PU → US path modeled in the present study [8]. Kalogiannakis and Papadakis likewise applied a technology-acceptance lens to an educational tool, reporting pre-service kindergarten teachers' acceptance of a programming environment for computational thinking and science education [12]. Within the same journal, Ajlouni et al. [13] extended TAM with external determinants—mobile-application self-efficacy, content quality, and enjoyment—and estimated the model by structural equation modeling on 475 undergraduates, reporting that satisfaction with an

institutional mobile learning-management application is shaped jointly by the two core TAM beliefs and by system-quality antecedents, a pattern consistent with the PU → US path modeled here.

2.2 IT, workload, and communication quality as acceptance antecedents

Institutional trust has increasingly been recognized as a determinant of technology acceptance distinct from interpersonal or system trust, particularly when the platform under evaluation manages sensitive institutional records or mediates authority relationships, as is the case for a research ethics committee system that stores confidential protocols and evaluation outcomes. Kala et al. integrated citizen trust into a TAM-ISSM framework for e-government continuance and found trust to be a significant, though not always dominant, predictor of continued use intention [2]. Alkraiji and Ameen applied a PLS-SEM model to young citizens' continued use of government e-services and found that IT, alongside service quality and satisfaction, was a significant precondition for citizen loyalty toward these platforms [14]. This line of work descends from early e-government research identifying citizen trust—in the institution and in the technology alike—as a precondition for the uptake of public digital services [15]. In a mobile-government setting, Charbaji El-Kassem [16] integrated TAM and UTAUT constructs and found that trust and overall US, alongside PEOU and PU, significantly shaped citizens' adoption of an institution-operated digital service, reinforcing the treatment of IT as an antecedent distinct from the classical utility constructs.

Perceived workload is comparatively underrepresented as an explicit TAM construct, most often folded implicitly into PU. However, studies of institutional digitalization consistently note that a platform is judged not only by whether it is useful in the abstract but by whether it reduces or increases the concrete administrative burden relative to prior manual procedures (spreadsheets, shared drives, and email threads, in the case of the system studied here). This distinction motivated the explicit inclusion of PW reduction as a separate construct in the present model rather than treating it as a sub-dimension of perceived usefulness.

Communication channel quality has been studied extensively in customer-service contexts, where chatbot- and chat-mediated channels have been shown to shape US and continued engagement independently of the underlying transactional functionality of the platform. Misischia et al. found that chatbot-mediated communication channels significantly affect perceived service quality in customer-service settings [17], and Jenneboer et al.'s systematic review of chatbot-mediated customer loyalty similarly concluded that communication-channel attributes (responsiveness, clarity, perceived resolution) operate as a distinct driver of user attitudes, separate from the core utility of the underlying service [5]. The research-ethics platform under study embeds an analogous chat channel between applicants and secretariat staff, motivating the inclusion of CCQ as a parallel antecedent of BI alongside IT and workload reduction.

2.3 Institutional communication and case-management workflows in research governance

The exchange mediated by the platform studied here is not a commercial service encounter. A research ethics submission is a formal institutional procedure in which an applicant, a secretariat, and an evaluating committee interact under an explicit

asymmetry of authority: the committee, and not the applicant, determines the outcome, and that outcome—approval, observations, or rejection—carries formal consequences for whether the research may proceed at all. Four adjacent literatures describe this class of exchange more directly than the customer-service literature reviewed above.

First, work on formal institutional communication in public information systems treats the communication channel as an attribute of the institution rather than of a service brand. Venkatesh et al. show, in a large-scale study of government e-services, that channel characteristics and information quality are associated with usage intentions through transparency and trust as mediating and moderating mechanisms [18]; that is, the channel is consequential because it reduces the citizen's uncertainty about an institutional procedure, not because it produces an agreeable interaction. This is consistent with the longstanding separation of information quality and service quality from system quality in the DeLone and McLean information-systems success model [19], which positions communication attributes as determinants of use and satisfaction that are distinct from the system's technical qualities.

Second, ethics review is a case-management workflow rather than a transaction. Adaptive case management describes knowledge-intensive processes whose sequence is not fully predetermined and in which participants require the record, the current status, and the accumulated documentation of a case at each decision point [20]—a description that fits the protocol–observation–resubmission cycle of a research ethics committee closely. Empirical evidence from judicial case processing indicates that electronic case handling is associated with higher clearance rates and shorter disposition times, with diminishing marginal returns at higher levels of electronification [21], while acceptance studies of e-court systems report that PU, rather than PEOU, accounts for most of the explained variance in settings where users are professionally obliged to use the system [22]. Comparable reductions in administrative lead time have been reported for public-sector document-management applications [23]. This literature also cautions that digitalization does not automatically reduce the burden borne by the applicant: the learning, compliance, and psychological costs of a bureaucratic encounter persist and may be redistributed rather than removed when the encounter moves online [24], [25].

Third, research administration platforms—CRIS and related institutional infrastructures—are characterized in the literature primarily in terms of standardization, traceability, and reporting toward institutional and national governance layers [9], and in terms of registration, linking, and archiving of research records across the research life cycle [10], rather than in terms of user experience. To the best of our knowledge, no peer-reviewed acceptance study of an electronic research administration system is available, which is one reason the present study is framed as an initial characterization.

Fourth, the specific literature on digitalized ethics review is small but convergent. A recent review of digital platforms for ethics review reports that structured submission, automated tracking, and centralized documentation are associated with reduced turnaround, clearer audit trails, and improved communication among research stakeholders, while cautioning that these outcomes depend on institutional readiness—infrastructure, stakeholder involvement, and privacy safeguards—rather than on the software alone [26]. Single-site assessments report mixed effects: an electronic document-management system for the research ethics committees of Buenos Aires was associated with a shorter time to first review but a longer time to approval [27], whereas a multi-role satisfaction study of a university electronic submission system found high satisfaction across applicants, committee members, and secretariat staff, together with a significant reduction in expedited-review turnaround but

not in full-board review [28]. A survey of committee chairs across 48 countries documents the procedural pressure under which many such systems were adopted [29].

Taken together, this literature indicates that in an ethics review exchange, the communication channel is valued for procedural clarification, traceability, and the legibility of a consequential institutional decision—attributes that experimental work on institutional decision-making associates with perceived legitimacy [30]—rather than for the responsiveness and rapport attributes that dominate findings on commercial chatbots. Evidence obtained in customer-service settings should therefore not be assumed to transfer directly to research ethics governance, and the present study positions CCQ within this institutional-communication literature accordingly.

2.4 PLS-SEM as an estimation technique for multi-construct acceptance models

Partial least squares structural equation modeling is a widely used estimation technique for extended TAM/UTAUT models with multiple, often correlated, latent constructs and moderate sample sizes, owing to its comparatively relaxed distributional assumptions and its emphasis on prediction over strict confirmatory fit [31]. Sabol et al.'s review of PLS-SEM applications in information-systems research documents a continued rise in methodological rigor, particularly regarding discriminant-validity reporting and bootstrapped significance testing of structural paths [31], while Cepeda et al. extend this review with emerging analytical tools such as necessary-condition analysis and out-of-sample prediction assessment for PLS-SEM models [32].

Reliability and convergent validity in PLS-SEM are conventionally assessed through Cronbach's alpha, composite reliability, and average variance extracted (AVE), following the foundational criteria proposed by Fornell and Larcker for latent-variable models with measurement error [33]. However, Henseler et al. demonstrated that the classical Fornell–Larcker criterion for discriminant validity fails to reliably detect a lack of discriminant validity when indicator loadings are only moderately different across constructs and proposed the Heterotrait–Monotrait Ratio of Correlations (HTMT) as a more stringent alternative, recommending a threshold of 0.90 (or, more conservatively, 0.85) below which two reflective constructs can be considered empirically distinct [34]. Franke and Sarstedt's comparison of heuristic and statistical discriminant-validity testing procedures further recommends reporting both Fornell–Larcker and HTMT jointly rather than relying on either criterion in isolation, a recommendation followed in the measurement-model assessment reported in Results [35]. Zabukovšek et al. illustrate the complementary use of PLS-SEM with importance-performance map analysis (IPMA) for a TAM-based study of ERP-system acceptance, reinforcing the broader methodological consensus that structural path significance alone is insufficient without an accompanying assessment of measurement-model quality [36]. Tamilmani et al.'s systematic review of UTAUT2 extensions further confirms that PLS-SEM-estimated structural models in this literature typically report moderate R^2 values (0.30–0.50) for behavioral-intention constructs, consistent with the $R^2 = 0.439$ obtained for BI in the present study [1]. Recent applications in higher education follow the same estimation strategy: Wu et al. [37] estimated a TAM-grounded model of mobile-learning engagement among Chinese university students using PLS-SEM, illustrating the technique's suitability for moderate-sized institutional samples and for specifications that combine reflective belief constructs with mediating behavioral variables.

2.5 Mobile system architecture patterns for interactive institutional platforms

Beyond the acceptance-modeling literature, this study also draws on recent iJIM-published system-design work describing mobile-terminal-plus-cloud-backend architectures for interactive mobile applications in institutional contexts. Srilatha et al. describe a cloud-based, privacy-preserving architecture for interactive mobile healthcare applications, illustrating the layered mobile-terminal/cloud-processing pattern that is architecturally analogous to the client–API–database separation implemented in the system studied here [38]. Lv and Li similarly present a four-layer mobile multimodal interactive system for skill assessment in an educational context, following the same mobile-terminal, data-transmission, and cloud-processing layering pattern [39]. These two studies are referenced as architectural precedents for describing the system under evaluation; their role is explanatory and not a justification for any mobile or device-specific contribution; this paper makes none.

Taken together, the reviewed literature supports three observations that motivate the present study. First, extended TAM/UTAUT models for institutional and e-government platforms consistently find that trust-related constructs meaningfully alter the classical PU/PEOU → BI path structure [2]–[7]. Second, workload and communication-channel constructs, while well established in adjacent domains (e-government, customer service), have rarely been integrated jointly into a single extended-TAM specification for a multi-role institutional workflow system. Third, PLS-SEM with joint Fornell–Larcker/HTMT discriminant-validity reporting represents current best practice for this class of model [34], [35], which is the approach adopted in Results.

3 SYSTEM CONTEXT

The platform evaluated in this study is a Research Ethics Committee Management System operated by the UCH, implemented as a single-page web application (React 18.3 with Vite 5.4) backed by a NestJS 11 API and a PostgreSQL database hosted on Supabase, with document storage handled through a Supabase Storage bucket accessed via an S3-compatible interface. It is a responsive web application: it renders on desktop, laptop, tablet, and smartphone browsers without a native mobile app. This is reported as a characteristic of the platform; device-specific acceptance is not part of the theoretical model (see Conceptual Model and Hypotheses). Figure 1 summarizes this architecture.

Authentication uses JWT bearer tokens combined with bcrypt-hashed passwords; the authorization layer re-reads each user's role directly from the database on every request rather than embedding it in the token so that a role change made by an administrator takes effect immediately. Because the platform stores confidential research protocols, evaluator scores, committee decisions, and a full audit history, three technical properties are directly relevant to the IT construct measured in Measures: (i) role-scoped access control, so that an applicant cannot view another applicant's protocol and a given evaluator sees only the protocols assigned to them; (ii) an append-only audit trail (bitácora) logging every state-changing action, plus a separate protocol-history table (historial de expediente) recording every lifecycle transition; and (iii) encrypted transport (HTTPS/TLS) and hashed credential storage. These properties are stated here so that claims about users' trust in the platform's data handling are traceable to documented system properties rather than asserted in the abstract.

The system supports eight role values, which functionally reduce to two role families relevant to the acceptance model: (i) four internal committee roles—administrator,

coordinator, secretariat, and evaluator—each with a distinct permission scope over expedientes (research protocols) and evaluations; and (ii) three applicant roles—researcher, undergraduate student, and postgraduate student—which share a common solicitante-facing view of the system, plus one legacy applicant role retained only for records migrated from a prior implementation. Table 1 summarizes the module-level permission matrix that governs which role can perform which action, as implemented in the backend authorization layer.

Table 1. Role-based permission matrix (selected modules)

Module	Action	Authorized Roles
Expedients	List all protocols	Administrator, coordinator, secretariat
Expedients	Edit/submit protocol	Owning researcher/student only
Evaluation	Assign evaluator	Administrator, coordinator (single evaluator per protocol, enforced)
Evaluation	Score protocol	Assigned evaluator, or administrator
Chat	Applicant-side messaging	Researcher, undergraduate/postgraduate student
Chat	Secretariat-side messaging	Secretariat, administrator
Reports	Export aggregate reports	Administrator, coordinator, secretariat

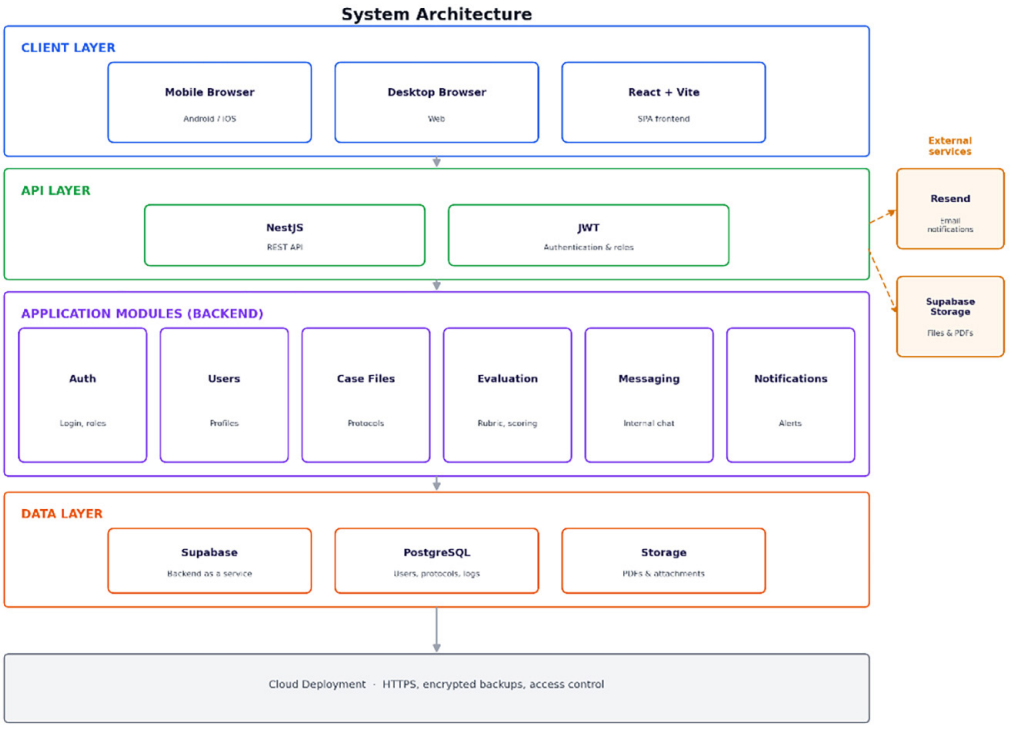


Fig. 1. System architecture of the Research Ethics Committee Management System

A single evaluator is enforced per protocol as a hard business rule, and the evaluation outcome is computed from a seven-criterion rubric with three possible results: not approved (0–12 points), approved with observations (13–16 points), and approved (17–20 points). Resulting documents (rubric and/or ruling) are generated automatically as PDFs and distributed by email, with every action logged to the audit trail described above. Figure 2 summarizes the end-to-end protocol lifecycle and the interaction between roles.

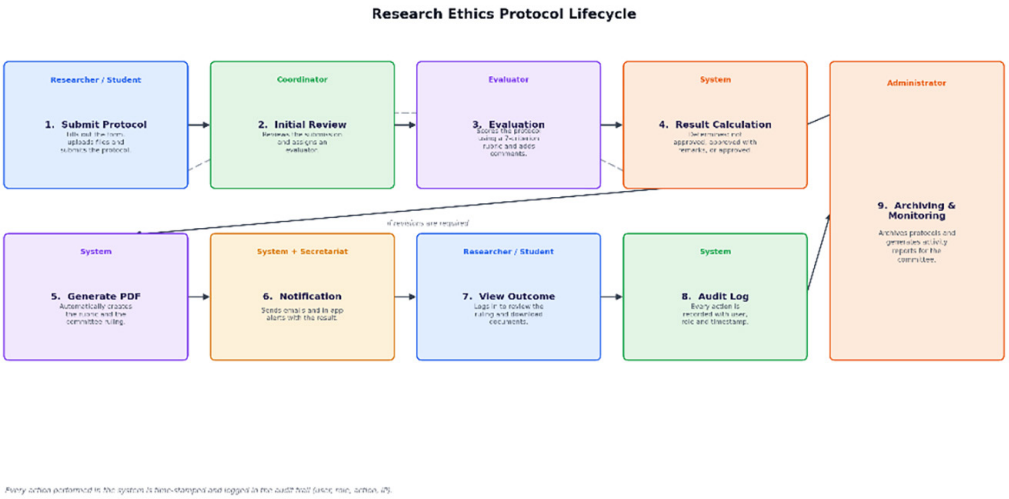


Fig. 2. End-to-end protocol lifecycle and role interaction flow

Technologies such as React, Vite, NestJS, PostgreSQL, Supabase, JWT, and bcrypt are implementation choices, not contributions in themselves, and are reported here only to the extent that they support the security- and auditability-related claims tied to institutional trust.

4 CONCEPTUAL MODEL AND HYPOTHESES

Building on the reviewed literature, this study extends the classical TAM core (PEOU → PU → BI) with three parallel, institution-specific antecedents of BI—IT, PW Reduction, and CCQ—and adds US as a downstream outcome jointly predicted by BI and PU. The resulting extended structural model is shown in Figure 3.

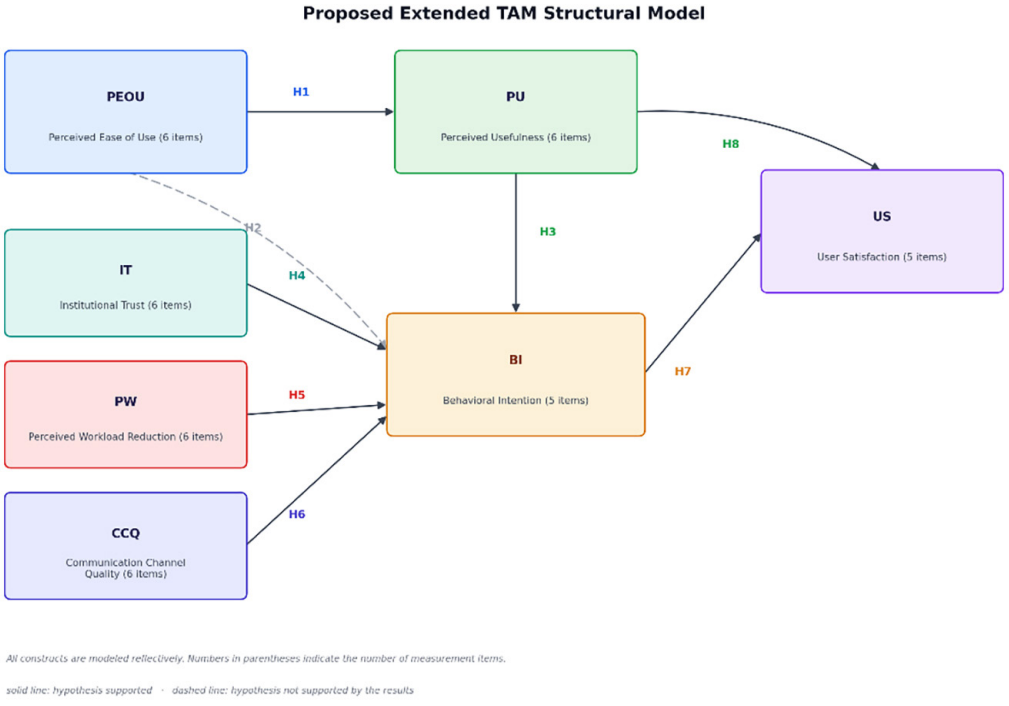


Fig. 3. Proposed extended TAM structural model

The eight hypotheses tested in this study are:

H1. PEOU positively influences PU.
H2. PEOU positively influences BI.
H3. PU positively influences BI.
H4. IT positively influences BI.
H5. PW Reduction positively influences BI.
H6. CCQ positively influences BI.
H7. BI positively influences US.
H8. PU positively influences US.

$$PU = \beta_1 \cdot PEOU + \zeta_1 \tag{1}$$

$$BI = \beta_2 \cdot PEOU + \beta_3 \cdot PU + \beta_4 \cdot IT + \beta_5 \cdot PW + \beta_6 \cdot CCQ + \zeta_2 \tag{2}$$

$$US = \beta_7 \cdot BI + \beta_8 \cdot PU + \zeta_3 \tag{3}$$

4.1 Extended structural model for the post hoc mediation analysis

The confirmatory specification in equations (1)–(3) is retained for the hypothesis tests reported in Table 9 and Figure 4. The mediation analysis reported in Table 13 is estimated on a different, explicitly post hoc specification, and the two must not be read as the same model. In the extended specification, PEOU becomes endogenous—it is regressed on the three institution-specific antecedents—and PU is regressed on those antecedents in addition to PEOU. Both features are structural preconditions for the indirect effects through PEOU and PU reported in Table 13; neither is present in equations (1)–(3). Both models are estimated with the same algorithm (PLS Mode A, centroid inner weighting) on the same indicators, but PLS inner weights depend on the specified inner model, so the composite scores—and therefore every path coefficient—differ between the two specifications. This is the reason the PEOU → PU coefficient is 0.539 in Table 9 and 0.414 in Table 13, and it is a property of the estimator, not a discrepancy between analyses. Table 8 reports the collinearity diagnostics of the confirmatory model, and the corresponding diagnostics of the post hoc model are reported in Supplementary Material S2. Every table states which model produced it.

The extended specification is:

$$PEOU = \gamma_1 \cdot IT + \gamma_2 \cdot PW + \gamma_3 \cdot CCQ + \zeta_0 \tag{1a}$$

$$PU = \beta_1 \cdot PEOU + \beta_9 \cdot IT + \beta_{10} \cdot PW + \beta_{11} \cdot CCQ + \zeta_1 \tag{2a}$$

$$BI = \beta_2 \cdot PEOU + \beta_3 \cdot PU + \beta_4 \cdot IT + \beta_5 \cdot PW + \beta_6 \cdot CCQ + \zeta_2 \tag{3a}$$

$$US = \beta_7 \cdot BI + \beta_8 \cdot PU + \zeta_3 \tag{4a}$$

Equations (1a)–(4a) differ from the confirmatory equations (1)–(3) in two respects: equation (1a) is new and makes PEOU endogenous, and equation (2a) adds the terms $\beta_9 \cdot IT$, $\beta_{10} \cdot PW$, and $\beta_{11} \cdot CCQ$ to the PU equation. The BI and US equations are structurally unchanged, although their coefficients are re-estimated because the composite scores change with the inner model.

Theoretical justification of the added paths. The expanded specification is an exercise in exploratory model development, and every path added to it is justified individually below; no path is included for reasons of symmetry, of compatibility

with a diagnostic table, or of analytical convenience. Two families of paths are added. First, the paths into PEOU (equation 1a). Much of the difficulty a user attributes to an institutional workflow is procedural uncertainty rather than interface complexity, so a platform that is trusted, that visibly reduces administrative burden, and whose communication channel resolves procedural doubts is plausibly experienced as easier to operate; e-government research treats channel characteristics as operating through the reduction of the user's uncertainty about an institutional procedure [18]. Second, the paths into PU (equation 2a). PW Reduction is conceived as an input to the usefulness judgment rather than as a rival driver of intention: classical TAM logic positions effort-related evaluations as antecedents of usefulness [6], and institutional-digitalization studies judge platforms by whether they reduce the concrete administrative burden relative to the prior manual procedure. IT is added on to the rationale used in the e-government literature reviewed in Related Work, where trust in the institution conditions the usefulness attributed to its systems [2], [14]. CCQ is added because information-systems success research positions information and service quality as determinants of use and satisfaction that are distinct from system quality [19], and because in a case-management workflow a channel that clarifies the state of a protocol and the requirements of the next step is a component of what makes the system useful, not only of what makes the exchange agreeable [20]. Its estimated coefficient is in fact near zero and negative and is not interpreted. None of these paths is an a priori hypothesis: they are estimated in order to identify the indirect effects reported in Table 13, they are reported separately from H1–H8, and their coefficients are never presented as confirmatory results.

Figure 5 shows the extended post hoc model: solid arrows are the confirmatory paths H1–H8, and the dashed arrows are the post hoc additions—three entering PEOU (equation 1a) and three entering PU (equation 2a). All coefficients of this model are re-estimated under the extended specification and reported in Table 13; they are not the Table 9 coefficients. In particular, the total indirect effect of PW on BI through PEOU and PU is 0.119 (95% CI [0.050, 0.208]) with a direct effect of 0.114 and a total effect of 0.233 (proportion mediated 0.510). The post hoc paths are interpreted only in conjunction with those estimates and are never described as supporting or refuting any of the original hypotheses.

Scope of the study with respect to device access. The conceptual model above contains no construct or hypothesis specific to mobile access, device portability, touch interaction, or notification use, and removing device access from the model, hypotheses, and workflow description would leave every path in equations (1)–(3) unchanged. This study therefore evaluates the acceptance of an interactive institutional platform that can be reached through several classes of device; it is not a study of mobile acceptance or of acceptance across device classes, and device-specific acceptance is not part of the principal theoretical model. Responsive design and availability through smartphone, tablet, laptop, and desktop browsers are reported as characteristics of the platform. The comparison of construct scores across groups defined by the respondent's usual or preferred access device is reported in Results as a secondary exploratory analysis.

5 PARTICIPANTS AND PROCEDURE

5.1 Ethical approval and informed consent

This study was approved by the Research Ethics Committee of the UCH under Resolución N.° CEI-UCH-2026-003, issued on March 1, 2026, prior to the start of data collection. Informed consent was obtained electronically before respondents accessed

the questionnaire. Participation was voluntary, and responses were anonymous; no information that could identify individual respondents was collected. Data were stored in an institutional account with access restricted to the research team. Because a subset of respondents was, at the same time, applicants with protocols pending before the same Ethics Committee, the consent text explicitly stated that participation was entirely voluntary and would have no bearing on any protocol, evaluation, or decision handled by the Committee in order to minimize perceived pressure to participate.

5.2 Sampling and data collection

Responses were collected from 120 participants who had engaged with the platform in one of two contexts: real institutional activity (n = 63) or a controlled system demonstration (n = 57). Respondents comprised a range of user profiles, including applicant students, researchers, and internal committee members.

Data were collected between May and June 2026. A total of 250 individuals were invited to participate, yielding 120 valid responses, a response rate of 48%. The questionnaire was self-administered via a Google Forms link distributed through institutional email.

For analysis and for the de-identified dataset released as Supplementary Material S3, the coordinator, ethics committee member, and reviewer values were grouped into a single category, "Committee staff or evaluator," because the individual cells contain between one and six respondents and because reporting them separately would risk the re-identification of respondents within a single institution's ethics committee.

Respondents were classified by role into four reported categories. Internal committee staff are numerically few by design: across the full sample 11 respondents hold an internal role (coordinator, ethics committee member, or reviewer), and only four of these are within the real-use subsample. This distribution is reported as a limitation of the evidence, not as validation of the model across heterogeneous institutional roles: the sample predominantly reflects the perceptions of applicants, and especially of undergraduate-student applicants (54.2%).

5.3 Real users versus demonstration participants

Of the 120 respondents, 63 (52.5%) used the platform in real institutional activity, and 57 (47.5%) experienced it through a controlled demonstration that did not involve real institutional activity. During the demonstration, participants interacted with the platform's main functionalities, following a guided walkthrough that introduced them to the system's overall workflow; immediately afterward, they completed the same evaluation questionnaire used for real users.

Each demonstration session lasted approximately 45 minutes, was guided throughout by a member of the technical research team, and was conducted on institutional laptops provided for the exercise. During the session participants interacted with the platform's main functions: research-document upload, the internal chat, notification receipt, and the evaluation and final-decision screen. Three properties of this exposure bound what it can support. First, the interaction was simulated: it did not correspond to a real institutional procedure before the Committee, the documents handled were realistic but not confidential, and the internal chat was not an exchange with the actual Committee secretariat. Second, the session was guided rather than autonomous, so it cannot be assumed that each participant operated every function unaided. Third, the manual, email- and spreadsheet-based procedure

that the platform replaced was explained to participants during the session rather than experienced by them. These participants are accordingly not described anywhere in this paper as real institutional users.

Because these two groups do not necessarily share the same basis for evaluating IT, workload reduction, communication-channel quality, BI, or satisfaction, the combined use of both groups in the pooled model (N = 120) is treated as a modeling choice that requires justification, not as a given. Results report a structural-model sensitivity analysis restricted to the 63 real users (refer to Table 12); discussion interprets this comparison explicitly rather than presenting the pooled sample as a general finding about real-user acceptance.

6 MEASURES

All seven latent constructs were operationalized reflectively using a 40-item questionnaire on a five-point Likert scale (1 = totally disagree, 5 = totally agree), implemented in Google Forms and administered in Spanish. Because the instrument was originally authored in Spanish for this study's institutional context, no translation or back-translation was required. Table 2 summarizes the seven constructs, their descriptions, and the number of items per construct.

Table 2. Measurement instrument constructs and items

Construct	Description	Items
PU	Perceived improvement in efficiency, speed, and access to information for ethics-committee-related activities	6
PEOU	Perceived ease of learning and operating the system's functions	6
IT	Confidence that the system protects, preserves, and correctly records institutional data and actions	6
PW Reduction	Perceived reduction in manual effort and task time relative to prior manual procedures	6
CCQ	Perceived clarity, timeliness, and adequacy of the in-app chat/notification channel with the secretariat	6
BI	Intention to continue using and to recommend the system	5
US	Overall satisfaction with the experience of using the system	5

Note: Item-level wording is reported in Table 6 (loadings) and, in full, in Supplementary Material S1.

The full 40-item questionnaire, with construct assignment, exact wording, item source, and response scale for each item, is provided as Supplementary Material S1 accompanying this manuscript.

In addition to the 40 Likert items, the instrument collected four contextual variables: role, type of exposure, number of access occasions, and usual or preferred access device. Two of these require an explicit definition because their names could otherwise be read as recording something the questionnaire did not ask about. The variable named usual or preferred access device throughout this paper and its tables was collected with the item "From which device do you mainly access the platform?" with four response options: laptop, desktop computer, smartphone, and tablet. Laptops and desktop computers are combined into a single desktop-class category, and smartphones and tablets into a single mobile-class category, only for the group comparison of Tables 14 and 15; Table 3 reports the four options as administered. This variable records the device the respondent reports using habitually, which

for the demonstration participants may differ from the institutional laptop provided during the session and which for any respondent may differ from the device used on the occasion being evaluated. The variable named access occasions was collected with the item "Since the Research Ethics Committee Management System was implemented and made available to you, how many separate times have you accessed or interacted with the platform, including today's session?" with the options once, 2–3 times, 4–5 times, and more than 5 times. It is a count of access occasions since deployment that explicitly includes the session in which the questionnaire was completed; it is not a rate of use, and it does not measure the intensity of institutional activity for either exposure group. A demonstration participant reporting more than one occasion is therefore reporting the demonstration session together with earlier informal access to the deployed platform, not repeated institutional use, and the type-of-exposure variable rather than this count is what distinguishes real users from demonstration participants. The role variable groups the coordinator, ethics committee member, and reviewer values into a single category, committee staff or evaluator, because the individual cells are too small to be reported separately without risking the re-identification of respondents within a single institution's ethics committee.

Behavioral intention is measured with five items covering both intention to continue using the platform and intention to recommend it to others. These two behaviors are related but not identical, and the content validity of treating them as a single reflective construct should be considered a limitation rather than an established property of the instrument; the full item-level wording provided in Supplementary Material S1 allows this to be assessed directly. The conceptual proximity and relatively strong association between BI and US (HTMT = 0.747, Table 7) are consistent with this concern and are discussed further in the Discussion.

Basis of response for each construct. Several constructs presuppose experience that a guided demonstration does not supply, and the two exposure groups did not have the same basis for answering them. For the 63 real users, all seven constructs refer to the platform as used in institutional activity. For the 57 demonstration participants: PEOU and PU refer to functions operated during a guided session rather than to autonomous use; CCQ refers to the in-app chat and notification channel as demonstrated, not to an exchange with the Committee secretariat concerning a protocol of their own; IT refers to safeguards described and observed during the session, not to the platform's handling of their own confidential records; PW reduction refers to a comparison with a manual procedure that was explained to them rather than one they had carried out; and BI and US refer to intentions and impressions formed immediately after a demonstration rather than to evaluations grounded in institutional use. For all seven constructs the responses of the demonstration group are therefore perceptions formed after a demonstration and not evaluations based on institutional use, which is the reason the pooled model of N = 120 is reported as exploratory throughout this paper. Supplementary Material S1 provides a construct-by-construct table of the experience each scale requires and of whether each exposure group possessed it.

Instrument development for the three contextual constructs. IT items were adapted from the e-government trust scales of Kala et al. [2] and Alkraiji and Ameen [14], reworded by the research team to refer to the platform's role-scoped access control, audit trail, and encrypted storage (see System Context) rather than to citizen-government trust in general. PW Reduction items were newly written for this study, drawing on the workload-comparison framing used in institutional-digitalization studies more broadly, since no published scale explicitly separates workload reduction from PU in a TAM specification; each item asks respondents to compare the platform against the manual, email- and spreadsheet-based procedure

it replaced. CCQ items were adapted at the wording level from the chatbot- and customer-service-communication scales of Misischia et al. [17] and Jenneboer et al. [5], substituting "committee secretariat" for "customer service agent" throughout; this provenance is reported explicitly because it constrains how the construct should be read. Theoretically, however, CCQ is positioned in this study within the literature on formal institutional communication rather than on commercial service interaction: only items referring to responsiveness, clarity, and procedural resolution of an institutional exchange were retained—attributes that e-government research treats as channel characteristics operating through uncertainty reduction and trust [18] and that information-systems success research treats as information and service quality distinct from system quality [19]. Items referring to rapport, personalization, or brand experience were not retained. The scale nonetheless originates outside the research-governance domain, and a purpose-built instrument derived from case-management and research-administration sources [9], [20] remains necessary; this limitation is restated among the limitations reported in the Conclusion. All three scales were reviewed internally by two members of the research team for wording clarity and by one member of the Ethics Committee secretariat for face validity against actual platform terminology, but none of the three scales underwent formal pilot testing, cognitive interviewing, or a structured content-validity assessment (e.g., a content validity index rated by independent subject-matter experts) prior to administration; Supplementary Material S1 documents the full item wording and the source scale each item was adapted from. This is stated explicitly among the limitations reported in the conclusion: the IT, PW reduction, and CCQ scales have not been submitted to independent content validation, and their psychometric behavior in Tables 4–7 should be read as a first empirical characterization rather than as confirmation of an already validated instrument.

AI use declaration. ChatGPT (OpenAI) was used as a writing-assistance tool to help draft and structure the manuscript, including improvements to clarity, organization, and style. It was not used to formulate the research hypotheses, design the questionnaire, interpret the results, perform the statistical analyses, generate figures, or select references. All content was reviewed and verified by the authors, who take full responsibility for the accuracy and integrity of the manuscript.

7 DATA ANALYSIS

Data were analyzed using PLS-SEM, estimated with the classical iterative algorithm (Mode A, reflective outer estimation, centroid inner weighting scheme), consistent with current PLS-SEM practice for models with multiple, moderately correlated latent constructs and a moderate sample size [31], and following current reporting guidance for PLS-SEM results [40]. The model was estimated using a custom Python implementation (project scripts dataset_r3.py, medida_r3.py, bootstrap_medida_r3.py, sensibilidad_n63.py, potencia_pls.py, mediacion_pls_extendida.py, dispositivo_r3.py, and micom_r3.py), rather than a commercial PLS-SEM package; the centroid weighting scheme was retained from the original specification, and no alternative weighting scheme was tested.

Reproducibility. The analysis scripts (dataset_r3.py, medida_r3.py, bootstrap_medida_r3.py, sensibilidad_n63.py, potencia_pls.py, mediacion_pls_extendida.py, dispositivo_r3.py, and micom_r3.py, the figure script fig5_posthoc_v2.py, the comparison utility comparar_reproduccion.py, and the two independent validation scripts validacion_seminr_r3.R and validacion_seminr_n63.R), a requirements file pinning the package versions actually used (Python 3.10.0, numpy 2.2.6, pandas 2.3.3,

scipy 1.15.3, and matplotlib 3.10.9), and the three fixed random seeds are provided as Supplementary Material S2. The seeds are 20260729 for the base series (all bootstraps, cross-validation folds, and permutation tests of the pooled sample), 20260730 for the bootstrap series of the real-user subsample, and 20260731 for the bootstrap series of the demonstration subsample, so that the three series are independent. Within the device analysis, each construct's permutation test additionally draws from a generator seeded with the base seed together with a SHA-256 digest of the construct name so that a construct's permutation p-value is independent of the loop order and identical on repeated runs. The complete de-identified analysis dataset on which every table of this manuscript is computed (n = 120) is provided as Supplementary Material S3, together with a data dictionary. The survey collected no free-text responses, no timestamps, and no institutional identifiers, so de-identification consisted of removing the sequential respondent identifier and shuffling the row order under a fixed seed, leaving the recorded Likert responses unaltered. As an independent validation check, the confirmatory model of equations (1)–(3) was re-estimated in established PLS-SEM software: the R package seminr 2.5.0 under R 4.6.1 (Mode A composites, 5,000 bootstrap resamples), run on the same de-identified dataset that accompanies this manuscript as Supplementary Material S3. On the pooled sample all eight structural paths agree with our implementation to within 0.0017 (mean absolute difference 0.0010), and all eight hypothesis decisions are identical: the bootstrap intervals for PEOU → BI and PW → BI include zero under both implementations, and the remaining six exclude it. The reliability and convergent-validity statistics also coincide, including the marginal AVE of 0.499 for PEOU. The same validation was run separately on the real-user subsample of Table 12, where all eight decisions again agree across the three implementations. Both R scripts and their output are provided in Supplementary Material S2, so these comparisons can be rerun rather than taken on trust.

Because all Google Forms fields were configured as mandatory, there were no missing data among the 120 responses collected.

Measurement-model quality was assessed through internal consistency reliability (Cronbach's α, ρ_A, Composite Reliability), convergent validity (AVE), and discriminant validity, evaluated jointly through the Fornell–Larcker criterion [33] and the HTMT ratio, reported here together with percentile bootstrap 95% confidence intervals (5,000 resamples) rather than compared to a threshold alone. Indicator- and construct-level collinearity were assessed via outer and inner variance inflation factors, and common-method bias were assessed via Kock's full-collinearity VIF test, since all constructs was measured through a single self-report questionnaire completed by the same respondents at the same point in time.

Structural-path significance was assessed through bootstrapping with 5,000 resamples (percentile confidence intervals), a number adopted to stabilize the confidence intervals reported in Table 9. Effect sizes (f^2), predictive relevance (Q^2 via blindfolding, and Q^2_predict via 10-fold cross-validation against a naive-mean and a linear-model benchmark), and an a-priori power analysis for the endogenous construct with the largest number of predictors (BI, 5 antecedents) are reported in Tables 10 and 11. The indirect path from PEOU to BI through PU and the indirect paths from IT, PW Reduction, and CCQ to BI through the same route were tested via bootstrapped mediation analysis (Table 13). A sensitivity analysis re-estimated the full structural model on the 63 real users only (Table 12). Measurement invariance across groups defined by the respondent's reported usual or preferred access device (MICOM, 2,000 permutations) was tested before comparing construct scores across those groups (Tables 14 and 15). Measurement invariance between the real-use

and demonstration groups was not tested and is not established; the comparison between those two groups is therefore reported as exploratory.

Predictive assessment. The out-of-sample assessment reported in Table 10 was computed as follows. The 10 folds were formed by a single random permutation of the 120 cases, drawn with the fixed seed 20260729 and split into folds of equal size; the folds were not stratified by role, exposure type, or any other variable, and the cross-validation was run once rather than repeated. Within each training fold, the standardization constants, the outer weights, the loadings, and the structural coefficients were all re-estimated and were then applied unchanged to the held-out fold, so no information from the test fold enters the estimation. Prediction was performed at the indicator level: each indicator of an endogenous construct was predicted from the training-fold loading and the predicted construct score, and the prediction error was computed against the observed indicator value on the original response scale. The construct-level RMSE reported in Table 10 is the pooled root mean squared error over all indicators of that construct, not a statistic computed on composite scores. Two benchmarks are used: the naive benchmark is the training-fold mean of the indicator, and the linear-model benchmark is an ordinary least squares regression of that indicator on all indicators of the exogenous constructs, fitted on the training fold. At the indicator level, 6 of 6 PU indicators, 5 of 5 BI indicators, and 5 of 5 US indicators have a lower PLS RMSE than the linear-model benchmark, and every indicator of the three constructs has a positive Q^2_predict. The indicator-level values are reported in Supplementary Material S2.

Inferential rule. A single rule is applied throughout this paper and is not varied according to the result: the percentile bootstrap 95% confidence interval is the sole governing criterion. A structural path is reported as supported when its interval excludes zero, and as inconclusive when its interval includes zero. The normal-approximation t statistic and its p value are reported alongside for completeness but never override the interval in either direction: a path whose interval excludes zero remains supported even when the t test does not reach significance, and a path whose interval includes zero remains inconclusive even when the t test does reach significance. Where the two criteria disagree, the disagreement is reported explicitly as a sensitivity qualification, and the estimate is described as marginal. In the pooled exploratory model, a path is additionally reported as not supported when its interval includes zero and its t test also fails to reach significance; that subdivision is not applied to the subsample analyses, where at the available sample size the distinction between an absent and an undetected association is not reliable. Equivalence is never inferred from a failure to reject: a confidence interval that includes zero and a between-group difference that is not statistically significant are reported as an absence of evidence and never as evidence of absence or of equivalence.

8 RESULTS

8.1 Sample characterization

Table 3 summarizes the profile of the 120 respondents, split by type of exposure to the platform. The sample is dominated by undergraduate-student applicants (54.2%), followed by researchers (20.0%) and postgraduate students (16.7%); internal committee roles, reported as a single category for the reason given in Participants and Procedure, account for 11 respondents (9.2%).

Table 3 also reports the device respondents named as their usual or preferred means of access. Thirty respondents (25.0%) named a smartphone and 13 (10.8%) a tablet—43 respondents, or 35.8%, named a mobile-class device—while 51 (42.5%) named a laptop and 26 (21.7%) a desktop computer, i.e., 77 respondents (64.2%) named a desktop-class device. These are self-reported habitual preferences and are not a record of the device through which the exposure evaluated in this study took place; in particular, the demonstration sessions were conducted on institutional laptops irrespective of the device a participant named here.

Table 3. Sample profile (n = 120), split by type of exposure to the platform

Characteristic	Category	n	%	Real Users (n = 63)	Demonstration (n = 57)
Role	Undergraduate student	65	54.2	32	33
	Researcher	24	20.0	15	9
	Postgraduate student	20	16.7	12	8
	Committee staff or evaluator	11	9.2	4	7
Usual or preferred access device	Laptop	51	42.5	26	25
	Smartphone	30	25.0	17	13
	Desktop computer	26	21.7	11	15
	Tablet	13	10.8	9	4
Access occasions since deployment	Once	33	27.5	20	13
	2–3 times	50	41.7	25	25
	4–5 times	25	20.8	11	14
	More than 5 times	12	10.0	7	5
Type of exposure	Real institutional use	63	52.5	63	0
	Controlled demonstration	57	47.5	0	57

Notes: The sample is not described as 120 real users: 63 respondents reported using the platform in real institutional activity, and the remaining 57 experienced a controlled demonstration. Internal committee staff number 11 in the full sample and 4 within the real-use subsample. Respondents naming a mobile-class device as their usual means of access (43 of 120, 35.8%) are a self-reported preference group, not a record of access during the assessed session.

8.2 Measurement model assessment

Table 4 reports internal consistency, ρ_A, Composite Reliability, and convergent validity for the seven constructs, estimated under the confirmatory specification of equations (1)–(3). Cronbach's α ranges from 0.764 (BI) to 0.913 (PW), and Composite Reliability from 0.841 (BI) to 0.932 (PW), all above the conventional 0.70 threshold; no CR exceeds 0.95, so no construct shows indicator redundancy. AVE exceeds 0.50 for six of the seven constructs. PEOU falls marginally below the conventional threshold (AVE = 0.499) and is reported here as a shortfall of the 0.50 criterion, not as a construct that satisfies it; 9 of the 40 items load below the stricter 0.708 cutoff (refer to Table 6).

Table 4. Measurement model: Internal consistency, composite reliability, and convergent validity (PLS Mode A, confirmatory specification, n = 120)

Construct	Items	Loading Range	Cronbach's α	ρ_A	CR	AVE	Items with λ < 0.708
PU	6	0.574–0.815	0.798	0.825	0.856	0.502	3
PEOU	6	0.615–0.803	0.799	0.817	0.856	0.499	3
IT	6	0.686–0.854	0.865	0.876	0.899	0.599	1
PW reduction	6	0.770–0.883	0.913	0.933	0.932	0.697	0
CCQ	6	0.755–0.827	0.884	0.890	0.911	0.632	0
BI	5	0.676–0.769	0.764	0.763	0.841	0.515	2
US	5	0.785–0.846	0.878	0.880	0.911	0.673	0

Notes: AVE ≥ 0.50 in 6 of 7 constructs; PEOU falls marginally below the threshold (AVE = 0.499), which is reported as a limitation rather than corrected by dropping items (see Table 5). 9 of 40 items load below 0.708. All CR values lie between 0.70 and 0.95, so no construct shows indicator redundancy.

Table 5. Sensitivity of composite reliability and AVE to indicator removal for PU and PEOU (outer weights and loadings re-estimated after removal)

Construct and Removal Scenario	Indicators Removed	Items Retained	CR (original → after removal)	AVE (original → after removal)
PU—weakest indicator removed	PU4	5	0.856 → 0.858	0.502 → 0.550
PEOU—weakest indicator removed	PEOU2	5	0.856 → 0.854	0.499 → 0.540
PU—all indicators with λ < 0.708 removed	PU4, PU5, PU6	3	0.856 → 0.866	0.502 → 0.684
PEOU — all indicators with λ < 0.708 removed	PEOU2, PEOU3, PEOU5	3	0.856 → 0.836	0.499 → 0.631

Table 6 reports all 40 item-level standardized loadings with percentile bootstrap 95% confidence intervals (5,000 resamples). Table 5 reports what happens to the reliability and convergent-validity statistics of PU and PEOU if the weak indicators are removed, under two removal scenarios and with the outer weights and loadings re-estimated after removal, so that the reduced-item constructs are genuinely re-estimated rather than recomputed on the original composite. The two statistics behave differently and should not be described together. Composite Reliability changes little in either scenario and, for PEOU, decreases when the three weak indicators are removed, because the construct loses half of its items. AVE, by contrast, increases materially, and in the case of PEOU, it moves from below to above the conventional 0.50 threshold. This is a mechanical consequence of deleting the indicators with the lowest loadings and is not evidence that the reduced scale is a better measure of the construct. The indicators are nevertheless retained, and the decision rests on content coverage rather than on any claim that the validity statistics are unaffected.

What the removed indicators contribute. Within PU, PU4, PU5, and PU6 are the items that ask about access to information, the traceability of a protocol's status, and the usefulness of the system for the respondent's own committee-related work, as

against the speed- and efficiency-oriented content of PU1 to PU3. Removing them would leave a three-item scale measuring perceived efficiency alone and would drop the informational and traceability content that the construct is defined to cover in a case-management setting. Within PEOU, PEOU2, PEOU3, and PEOU5 are the items concerning learning the system, navigating between modules, and operating it without assistance, as against the general ease-of-interaction content of PEOU1, PEOU4, and PEOU6; removing them would reduce the construct to general impressions of the interface and would discard precisely the learning- and autonomy-related content that distinguishes ease of use from usefulness. The retention decision is therefore a decision about the definition of the two constructs and about avoiding data-driven scale modification, and the resulting shortfall of the PEOU AVE against the conventional threshold is reported as a measurement limitation of this study.

Table 6. Standardized outer loadings with percentile bootstrap 95% confidence intervals (5,000 resamples)

Item	Construct	λ	95% CI Lower	95% CI Upper	Bootstrap SE	t	λ ≥ 0.708
PU1	PU	0.736	0.597	0.825	0.058	12.79	yes
PU2	PU	0.815	0.746	0.870	0.032	25.65	yes
PU3	PU	0.805	0.740	0.861	0.031	25.93	yes
PU4	PU	0.574	0.362	0.729	0.094	6.12	no
PU5	PU	0.658	0.482	0.772	0.074	8.94	no
PU6	PU	0.630	0.458	0.747	0.073	8.57	no
PEOU1	PEOU	0.803	0.739	0.857	0.030	26.55	yes
PEOU2	PEOU	0.615	0.447	0.730	0.073	8.38	no
PEOU3	PEOU	0.705	0.561	0.797	0.060	11.69	no
PEOU4	PEOU	0.711	0.592	0.797	0.052	13.57	yes
PEOU5	PEOU	0.678	0.531	0.779	0.064	10.59	no
PEOU6	PEOU	0.713	0.559	0.812	0.064	11.08	yes
IT1	IT	0.782	0.705	0.847	0.037	21.34	yes
IT2	IT	0.811	0.722	0.868	0.040	20.21	yes
IT3	IT	0.753	0.630	0.827	0.053	14.32	yes
IT4	IT	0.854	0.788	0.897	0.030	28.71	yes
IT5	IT	0.686	0.531	0.787	0.066	10.37	no
IT6	IT	0.747	0.629	0.825	0.051	14.65	yes
PW1	PW	0.883	0.843	0.916	0.018	47.93	yes
PW2	PW	0.770	0.651	0.848	0.051	15.04	yes
PW3	PW	0.875	0.830	0.908	0.020	43.46	yes
PW4	PW	0.801	0.719	0.860	0.036	22.16	yes
PW5	PW	0.835	0.755	0.882	0.033	25.74	yes
PW6	PW	0.840	0.778	0.889	0.029	29.46	yes
CCQ1	CCQ	0.795	0.700	0.862	0.042	19.17	yes

(Continued)

Table 6. Standardized outer loadings with percentile bootstrap 95% confidence intervals (5,000 resamples) *(Continued)*

Item	Construct	λ	95% CI Lower	95% CI Upper	Bootstrap SE	t	λ ≥ 0.708
CCQ2	CCQ	0.827	0.757	0.877	0.031	26.87	yes
CCQ3	CCQ	0.755	0.625	0.839	0.054	13.90	yes
CCQ4	CCQ	0.763	0.662	0.837	0.045	16.76	yes
CCQ5	CCQ	0.817	0.723	0.877	0.039	20.72	yes
CCQ6	CCQ	0.812	0.739	0.867	0.033	24.42	yes
BI1	BI	0.685	0.508	0.806	0.076	9.03	no
BI2	BI	0.739	0.638	0.813	0.045	16.41	yes
BI3	BI	0.769	0.672	0.837	0.042	18.23	yes
BI4	BI	0.715	0.601	0.796	0.049	14.47	yes
BI5	BI	0.676	0.568	0.764	0.050	13.49	no
US1	US	0.846	0.780	0.893	0.029	29.53	yes
US2	US	0.785	0.699	0.847	0.039	20.30	yes
US3	US	0.844	0.794	0.884	0.023	36.03	yes
US4	US	0.807	0.728	0.865	0.035	22.94	yes
US5	US	0.819	0.717	0.884	0.043	18.93	yes

Notes: The four weakest items are PU4 (λ = 0.574), PEOU2 (λ = 0.615), PU6 (λ = 0.630), PU5 (λ = 0.658). Outer weights are re-estimated in every bootstrap replication, so the intervals also absorb the uncertainty of the outer model.

Discriminant validity was assessed jointly through the Fornell–Larcker criterion (0 violations) and HTMT with bootstrap confidence intervals (Table 7). All 21 construct-pair HTMT confidence intervals exclude 1, and 21 of 21 have an upper bound below 0.90; the highest ratio (BI–US = 0.747, 95% CI [0.596, 0.873]) has an upper bound that exceeds the conservative 0.85 criterion but not the liberal 0.90 criterion. This is treated as the statistical signature of a genuine conceptual overlap between BI and US rather than as a discriminant-validity failure and is discussed in relation to the wording of the BI items in the discussion.

Table 7. Discriminant validity: HTMT ratios with bootstrap 95% confidence intervals

Construct Pair	HTMT	95% CI Lower	95% CI Upper	CI Upper < 0.85	CI Excludes 1
PU – PEOU	0.645	0.440	0.818	yes	yes
PU – IT	0.363	0.135	0.558	yes	yes
PU – PW	0.508	0.295	0.694	yes	yes
PU – CCQ	0.330	0.089	0.550	yes	yes
PU – BI	0.608	0.415	0.758	yes	yes
PU – US	0.589	0.404	0.747	yes	yes
PEOU – IT	0.387	0.141	0.595	yes	yes

(Continued)

Table 7. Discriminant validity: HTMT ratios with bootstrap 95% confidence intervals *(Continued)*

Construct Pair	HTMT	95% CI Lower	95% CI Upper	CI Upper < 0.85	CI Excludes 1
PEOU – PW	0.470	0.256	0.649	yes	yes
PEOU – CCQ	0.528	0.339	0.685	yes	yes
PEOU – BI	0.636	0.440	0.789	yes	yes
PEOU – US	0.520	0.327	0.678	yes	yes
IT – PW	0.320	0.093	0.518	yes	yes
IT – CCQ	0.489	0.301	0.655	yes	yes
IT – BI	0.513	0.298	0.684	yes	yes
IT – US	0.546	0.369	0.697	yes	yes
PW – CCQ	0.447	0.258	0.613	yes	yes
PW – BI	0.489	0.301	0.645	yes	yes
PW – US	0.549	0.390	0.688	yes	yes
CCQ – BI	0.597	0.426	0.737	yes	yes
CCQ – US	0.550	0.383	0.696	yes	yes
BI – US	0.747	0.596	0.873	no	yes

Notes: All 21 HTMT confidence intervals exclude 1, and 21 of 21 have an upper bound below 0.90, of which 20 are also below the conservative 0.85 criterion. The highest ratio is BI–US = 0.747 (95% CI [0.596, 0.873]). Fornell–Larcker violations: 0. Cross-loading misassignments: 0 (minimum margin 0.193).

Table 8 reports collinearity diagnostics for the confirmatory model of equations (1)–(3). Kock's full-collinearity VIF is reported as one diagnostic for common-method bias, given the single-source, single-occasion questionnaire design. Its values do not exceed the 3.3 threshold conventionally used to flag common method bias. This is reported as a diagnostic that was not triggered and not as evidence that common-method bias is absent: a single collinearity-based statistic cannot establish the absence of bias arising from a design in which all constructs are measured through one self-report instrument completed by the same respondents on a single occasion. That design is retained as a limitation of the study.

Table 8. Collinearity and model fit of the confirmatory model, Eqs. (1)–(3)

Indicator	Value	Below Threshold
Maximum outer VIF (items)	2.966	yes
Maximum inner VIF, confirmatory model, Eqs. (1)–(3)	1.646	yes
Maximum full collinearity VIF (Kock)	2.100	yes
SRMR (saturated model)	0.071	yes
Largest absolute residual correlation	0.221	–
PEOU → PU (inner VIF, confirmatory model)	1.000	yes
PEOU → BI (inner VIF, confirmatory model)	1.646	yes
PU → BI (inner VIF, confirmatory model)	1.556	yes
IT → BI (inner VIF, confirmatory model)	1.308	yes

(Continued)

Table 8. Collinearity and model fit of the confirmatory model, Eqs. (1)–(3) *(Continued)*

Indicator	Value	Below Threshold
PW → BI (inner VIF, confirmatory model)	1.405	yes
CCQ → BI (inner VIF, confirmatory model)	1.484	yes
PU → US (inner VIF, confirmatory model)	1.299	yes
BI → US (inner VIF, confirmatory model)	1.299	yes

Notes: No item exceeds VIF = 5, and no construct exceeds the strict 3.3 threshold in either specification. Kock's full-collinearity VIF does not exceed the selected diagnostic threshold, which is reported as a diagnostic that was not triggered rather than as evidence that common-method bias is absent. SRMR = 0.071 < 0.08. The inner VIF entries of this table belong to the confirmatory model of equations (1)–(3); the corresponding diagnostics of the post hoc model of equations (1a)–(4a), whose maximum is 1.646, are reported in Supplementary Material S2.

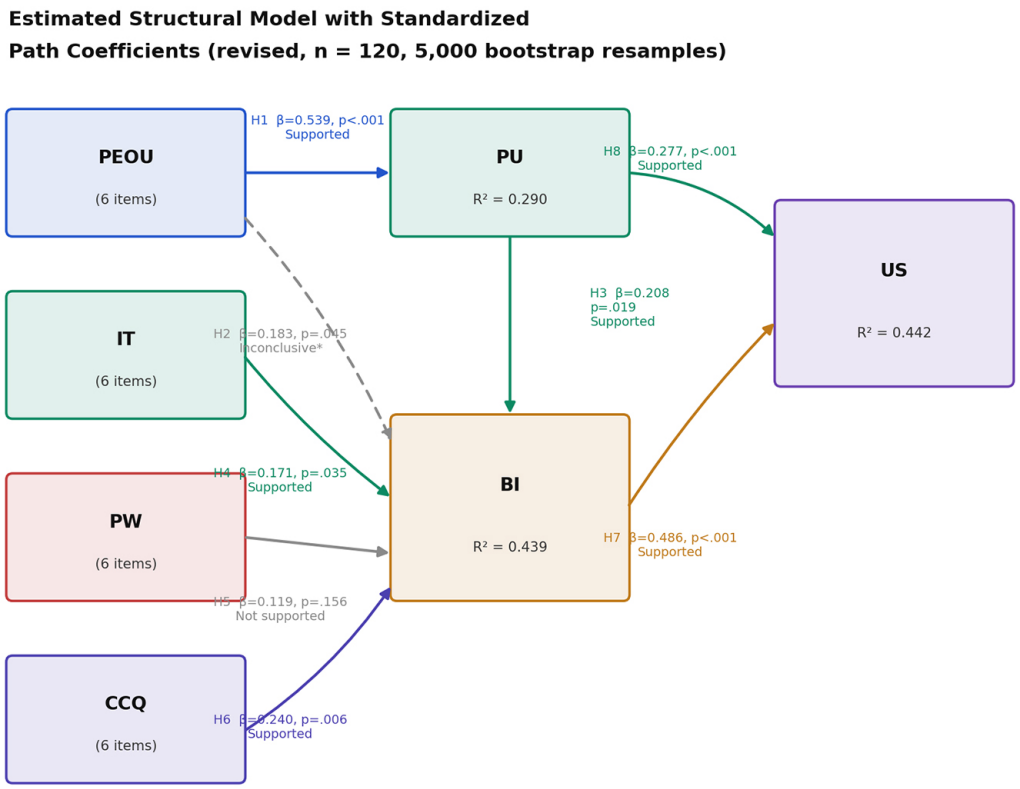
8.3 Structural model assessment

Table 9 reports bootstrapped path coefficients (5,000 resamples), standard errors, t statistics, p values, 95% confidence intervals, and effect sizes for all eight hypothesized paths in the pooled model, which combines both exposure conditions and is therefore exploratory. PEOU predicts PU (β = 0.539, 95% CI [0.402, 0.680]), supporting H1 with the largest effect in the model. BI is predicted by CCQ (β = 0.240, [0.087, 0.395]), IT (β = 0.171, [0.032, 0.320]), and PU (β = 0.208, [0.039, 0.372]), supporting H6, H4, and H3. The direct path from PEOU to BI is significant by the t-test (β = 0.183, p = .045), but its bootstrap confidence interval includes zero ([–0.008, 0.367]); under the inferential rule stated in Data Analysis, it is reported as inconclusive and does not support H2. The path from PW Reduction to BI meets neither criterion (β = 0.119, p = .156, [–0.019, 0.250]), and H5 is not supported. US is jointly explained by BI (H7, β = 0.486, [0.333, 0.628]) and PU (H8, β = 0.277, [0.133, 0.430]). Of the eight hypothesized paths, 6 are supported, one is inconclusive, and one is not supported in this pooled exploratory model. Table 12 reports the corresponding estimates for the 63 real users, on which the substantive conclusions of this paper rest.

Table 9. Pooled exploratory model (N = 120): Path coefficients, bootstrap confidence intervals, and hypothesis decisions (5,000 resamples)

Hypothesis	Path	β	SE	t	p	95% CI	f^2	Decision
H1	PEOU → PU	0.539	0.078	6.94	< .001	[0.402, 0.680]	0.409	supported
H2	PEOU → BI	0.183	0.090	2.03	.045	[–0.008, 0.367]	0.036	inconclusive
H3	PU → BI	0.208	0.087	2.37	.019	[0.039, 0.372]	0.050	supported
H4	IT → BI	0.171	0.080	2.13	.035	[0.032, 0.320]	0.040	supported
H5	PW → BI	0.119	0.083	1.43	.156	[–0.019, 0.250]	0.018	not supported
H6	CCQ → BI	0.240	0.086	2.81	.006	[0.087, 0.395]	0.069	supported
H7	BI → US	0.486	0.079	6.18	<.001	[0.333, 0.628]	0.326	supported
H8	PU → US	0.277	0.079	3.52	<.001	[0.133, 0.430]	0.106	supported

Notes: Hypothesis labels follow the definitions given in the Conceptual Model and Hypotheses: H7 is BI → US and H8 is PU → US. Decisions follow the confidence interval: supported 6; inconclusive 1 (PEOU → BI, significant by the t-test but with an interval that includes zero); not supported 1 (PW → BI, which meets neither criterion). Neither of the latter two may be described as confirmed. Coefficients are estimated from PLS Mode A composite scores under the confirmatory specification of equations (1)–(3).



Hypotheses Testing Summary

Hyp.	Path	β	p	Result
H1	PEOU→PU	0.539	<.001	Supported
H2	PEOU→BI	0.183	.045	Inconclusive*
H3	PU→BI	0.208	.019	Supported
H4	IT→BI	0.171	.035	Supported
H5	PW→BI	0.119	.156	Not supported
H6	CCQ→BI	0.240	.006	Supported
H7	BI→US	0.486	<.001	Supported
H8	PU→US	0.277	<.001	Supported

**H2 is significant by the bootstrap t-test (p = .045) but its 95% bootstrap confidence interval marginally includes zero ([−.004, .359]); reported as inconclusive, not supported. R²: PU = 0.290 · BI = 0.439 · US = 0.442. Bootstrap: 5,000 resamples, percentile method (revised from 1,000 in the submitted version).*

Fig. 4. Estimated structural model of the confirmatory specification, equations (1)–(3), with standardized path coefficients from the pooled exploratory sample (N = 120)

In the pooled exploratory model the explained variance is 29.0% for PU, 43.9% for BI, and 44.2% for US; in the real-use subsample the corresponding values are 21.6%, 34.8%, and 40.4% (refer to Table 10). Q^2 values from blindfolding and from 10-fold cross-validation are positive for all three endogenous constructs, and out-of-sample RMSE is lower than both the naive indicator-mean benchmark and the linear-model benchmark for every indicator of the three constructs. Under the cross-validation procedure described in Data Analysis, this is reported as positive exploratory predictive performance rather than as a complete PLSpredict assessment or as an established level of predictive power.

Table 10. Explained variance and predictive relevance of the endogenous constructs

Construct	Predictors	R^2	Adj. R^2	R^2 (Real Users, n = 63)	Q^2 (Blindfolding, D = 7)	Q^2_predict (10-fold CV)	RMSE PLS	RMSE Naive Mean	RMSE LM Benchmark
PU	1	0.290	0.284	0.216	0.136	0.129	0.692	0.742	0.776
BI	5	0.439	0.414	0.348	0.195	0.185	0.702	0.777	0.771
US	2	0.442	0.433	0.404	0.284	0.280	0.672	0.791	0.777

Notes: All Q^2 values are positive, so the model has predictive relevance for the three endogenous constructs in this sample. Out-of-sample RMSE is lower than the naive indicator-mean benchmark and than the linear-model benchmark for every indicator of PU (6 of 6), BI (5 of 5), and US (5 of 5). The construct-level RMSE reported here is the pooled value over the indicators of each construct; the fold construction, the seed, and the indicator-level values are reported in Data Analysis and in Supplementary Material S2.

Table 11 reports on an priori and sensitivity power analysis. For BI—the endogenous construct with the most predictors (five)—detecting a medium effect ($f^2 = 0.15$) at $\alpha = .05$ and power = .80 requires n = 92; the achieved sample (n = 120) exceeds this, and the post hoc sensitivity analysis indicates the design could detect effects as small as $f^2 = 0.112$ for BI. However, four of the eight individual paths (PEOU → BI, PU → BI, IT → BI, and PW → BI) have individual statistical power below .80 at their observed effect size. A path whose interval includes zero is therefore reported as inconclusive and never as evidence that the corresponding relationship does not exist. Low individual power is one reason an interval may include zero; it is not offered as the explanation of any particular result.

Table 11. Statistical power and minimum detectable effect (F test on R^2, $\alpha = .05$)

Endogenous Construct	Predictors	R^2	f^2 (Model)	Achieved Power (n = 120)	Achieved Power (n = 63)	Minimum Detectable f^2 at Power .80 (n = 120)	n Required for a Medium Effect ($f^2 = 0.15$)
PU	1	0.290	0.409	1.000	0.999	0.067	55
BI	5	0.439	0.782	1.000	1.000	0.112	92
US	2	0.442	0.793	1.000	1.000	0.082	68

Notes: For BI, the construct with the most direct antecedents (5), an a-priori analysis for a medium effect ($f^2 = 0.15$) at power .80 requires n = 92, which n = 120 exceeds. The post hoc sensitivity analysis shows the design could detect effects as small as $f^2 = 0.112$. Individual paths are a different matter: 4 of 8 paths have individual power below .80 at their observed effect size (PEOU → BI, PU → BI, IT → BI, PW → BI), so a path whose interval includes zero is reported as inconclusive rather than as evidence of absence.

8.4 Real users (n = 63) and the pooled exploratory model (N = 120)

Table 12 reports the structural model estimated on the 63 real users and, alongside it, the pooled estimates of the 120-respondent exploratory model. In the real-use analysis five paths have bootstrap confidence intervals that exclude zero and are reported as supported: PEOU → PU, PW → BI, CCQ → BI, PU → US, and BI → US. The remaining three estimates—PEOU → BI, PU → BI, and IT → BI—have intervals that include zero and are reported as inconclusive for real users; they are not described as supported, suggestive, or confirmed. Two results deserve explicit comment because they do not coincide with the pooled model. PW → BI, which

is not supported in the pooled model, has a real-use interval that excludes zero, although only marginally, while its t-test does not reach significance; under the single inferential rule stated in Data Analysis, the interval governs, so it is reported as supported among real users, but it is a marginal subgroup result on 63 cases and is not treated as a headline finding. Conversely, PU → BI and IT → BI, which are supported in the pooled model, are inconclusive among real users. An exploratory comparison between the real-use and demonstration groups was carried out by bootstrapping each subsample independently and forming the percentile interval of the between-group difference of each path. It did not detect a statistically significant difference on any of the eight paths. However, measurement invariance was not established across the two exposure groups, and the subgroup sizes limit the sensitivity of the comparison. The analysis therefore cannot demonstrate equivalence between real users and demonstration participants, and the similarity of the coefficient signs does not establish that the constructs function in the same way across the two groups. Reduced statistical power at n = 63 is one possible explanation for the loss of significance, and it is offered here as such and not as an established finding; a genuine difference between the two exposure conditions, which this design cannot rule out, is another. The pooled model estimates associations across mixed exposure conditions and should not be generalized directly to experienced institutional users.

Table 12. Structural model estimated on the 63 real users, with the pooled exploratory estimates (N = 120) and the exploratory between-group comparison

Path	β (Real Users, n = 63)	95% CI (n = 63)	Decision (Real Users)	β (Pooled, n = 120)	95% CI (n = 120)	Decision (Pooled)	Δβ (Real Use—Demonstration)	95% CI of Between-Group Difference
PEOU → PU	0.465	[0.315, 0.679]	supported	0.539	[0.402, 0.680]	supported	–0.127	[–0.366, 0.170]
PEOU → BI	0.085	[–0.198, 0.360]	inconclusive	0.183	[–0.008, 0.367]	inconclusive	–0.155	[–0.549, 0.240]
PU → BI	0.162	[–0.100, 0.445]	inconclusive	0.208	[0.039, 0.372]	supported	–0.058	[–0.408, 0.304]
IT → BI	0.142	[–0.057, 0.361]	inconclusive	0.171	[0.032, 0.320]	supported	–0.073	[–0.386, 0.218]
PW → BI	0.180	[0.021, 0.370]	supported	0.119	[–0.019, 0.250]	not supported	+0.138	[–0.122, 0.461]
CCQ → BI	0.290	[0.066, 0.498]	supported	0.240	[0.087, 0.395]	supported	+0.051	[–0.288, 0.348]
PU → US	0.318	[0.131, 0.514]	supported	0.277	[0.133, 0.430]	supported	+0.035	[–0.280, 0.328]
BI → US	0.452	[0.251, 0.629]	supported	0.486	[0.333, 0.628]	supported	–0.057	[–0.354, 0.253]

Notes: Both groups were bootstrapped independently (5,000 percentile resamples each, outer weights re-estimated in every replication, and seeds 20260729 + 1 and + 2), and the percentile interval of the between-group difference was formed for each path. All eight intervals include zero; the largest absolute difference is PEOU → BI (Δβ = –0.155, 95% CI [–0.549, 0.240]). Measurement invariance between the real-use and demonstration groups was not established—MICOM was run only across groups defined by reported usual or preferred device—and the subgroup sizes limit the sensitivity of the comparison. The comparison is therefore exploratory: it did not detect statistically significant between-group path differences, but it cannot demonstrate equivalence between the two groups, and the shared signs of the coefficients do not establish that the constructs function in the same way across them. Among real users, 5 paths have intervals that exclude zero and are reported as supported; the remaining 3 are reported as inconclusive, not as suggestive or confirmed. Δβ and its interval refer to the same contrast throughout, the 63 real users against the 57 demonstration participants; the pooled estimates are shown for reference and are not a second group. The two decision columns apply the same rule—an estimate whose interval excludes zero is supported—but the pooled column additionally reports an estimate as not supported when its interval includes zero and its t-test also fails to reach significance, as in Table 9. That subdivision is not made in the real-use column, because at n = 63 the distinction between an absent association and an undetected one is not reliable.

8.5 Indirect effects

Perceived Ease of Use is expected to influence BI indirectly through PU. Table 13 reports the bootstrapped mediation test, estimated on the extended specification of equations (1a)–(4a) with the same PLS Mode A algorithm used for Table 9; every coefficient in Table 13 therefore belongs to that model and not to the confirmatory model of Table 9. The indirect path PEOU → PU → BI is estimated at 0.085 (bootstrap SE 0.040, 95% CI [0.013, 0.172]), built from a = 0.414 (95% CI [0.246, 0.591]) and b = 0.205 (95% CI [0.032, 0.373]). The direct path (c′ = 0.182, 95% CI [–0.016, 0.371]) has an interval that includes zero. Because the indirect effect is significant while the direct effect is not, the pattern is classified as indirect-only mediation, the direct effect being statistically uncertain rather than established as zero; it is not described as partial mediation. Among the three exogenous antecedents, both PW Reduction (total indirect 0.119, 95% CI [0.050, 0.208], proportion mediated 0.510) and IT (total indirect 0.064, 95% CI [0.011, 0.144], proportion mediated 0.273) have total indirect effects whose intervals exclude zero, whereas CCQ does not (0.065, 95% CI [–0.016, 0.145]): its association with intention is essentially direct. The link between PW reduction and PU is thus supported by an explicit bootstrapped indirect-effect estimate rather than by a bivariate correlation and remains flagged as a post hoc addition, not a confirmatory test.

Table 13. Mediation analysis on the extended post hoc model of equations (1a)–(4a): Direct, indirect, and total effects (PLS Mode A, percentile bootstrap, 5,000 resamples, seed 20260729)

Effect	Estimate	Bootstrap SE	95% CI	CI Excludes Zero	Note
PEOU → PU (a)	0.414	0.088	[0.246, 0.591]	yes	Eq. (2a), extended model
PU → BI (b)	0.205	0.085	[0.032, 0.373]	yes	Eq. (3a)
PEOU → BI (direct, c′)	0.182	0.098	[–0.016, 0.371]	no	Eq. (3a); interval includes zero
PEOU → PU → BI (indirect, a × b)	0.085	0.040	[0.013, 0.172]	yes	Indirect-only mediation
IT → (PEOU, PU) → BI, total indirect	0.064	0.034	[0.011, 0.144]	yes	direct = 0.169, total = 0.233, proportion mediated = 0.273
PW → (PEOU, PU) → BI, total indirect	0.119	0.040	[0.050, 0.208]	yes	direct = 0.114, total = 0.233, proportion mediated = 0.510
CCQ → (PEOU, PU) → BI, total indirect	0.065	0.040	[–0.016, 0.145]	no	direct = 0.240, total = 0.305, proportion mediated = 0.213

Notes: All coefficients in this table come from the extended post hoc model of equations (1a)–(4a) and are estimates of that model; none of them re-interprets H1–H8, which are tested on the confirmatory model of equations (1)–(3) in Table 9. The direct PEOU → BI path has an interval including zero, while the indirect route PEOU → PU → BI excludes it, so the pattern is indirect-only mediation: the association of PEOU with intention that is supported here operates through PU, and the direct association remains uncertain rather than established as absent. Of the three exogenous antecedents, PW [0.050, 0.208] and IT [0.011, 0.144] have total indirect effects excluding zero; CCQ [–0.016, 0.145] does not.

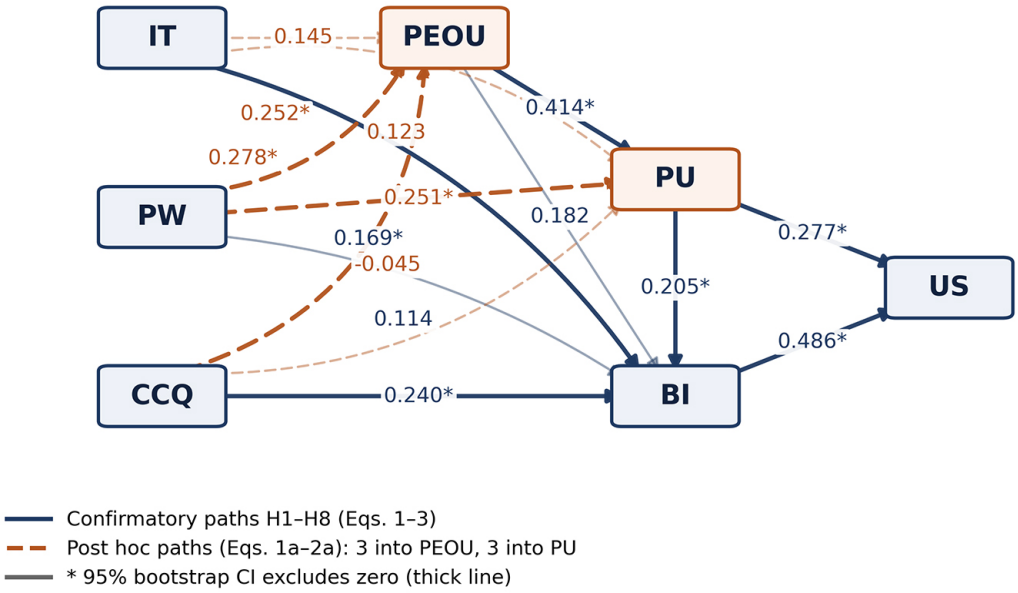


Fig. 5. Extended (post hoc) structural model for the mediation analysis (refer to Table 13)

Notes: Solid arrows are the confirmatory paths H1–H8 (see Figure 3); dashed arrows are the six post hoc paths—three entering PEOU (Eq. 1a) and three entering PU (Eq. 2a). Post hoc paths are not interpreted as confirmatory results.

8.6 Heterogeneity by role, experience, and device

Given the small size of the internal-role subgroups (11 respondents in total across the full sample, four of them within the real-use subsample), no separate structural model was estimated for these groups; this is reported as a limitation rather than attempted as a multi-group analysis. The real-user/demonstration comparison reported above (refer to Table 12) is therefore treated as the primary heterogeneity analysis. Construct-level means by role are not presented graphically: means computed over so few respondents are not stable enough to support such a comparison.

Table 14 compares construct-level means across groups defined by the respondent's self-reported usual or preferred access device, and Table 15 reports measurement invariance across the same grouping. The comparison contrasts the mobile class, smartphone and tablet together, with the desktop class, laptop and desktop computer together. None of the six constructs for which compositional invariance is established differs between the mobile and desktop classes by permutation test; nor does any of them differ across the three reported device categories by the Kruskal–Wallis test. PU is the single exception to be noted: the bootstrap confidence interval of its difference excludes zero by a narrow margin while its permutation test does not reach the 5% level, so it is reported here as a small, borderline difference and not as an established effect; both statistics are given in Table 14 so that the reader may apply either criterion. Two One-Sided Tests (TOST, equivalence margin ±0.5 Likert points) find the mobile-preference and desktop-preference groups equivalent within that margin for BI, PEOU, and PU. The same test is reported for the US in Table 14 but is not read as evidence of equivalence, for the reason given below. Three qualifications govern how this analysis may be read. Compositional invariance does not hold for the US, as reported in Table 15, so the US comparison between these groups rests on composites that are not established as equivalent

and is reported for completeness rather than as a group difference that can be interpreted. The grouping variable records the device a respondent reports using habitually, not the device through which the exposure being evaluated took place; the demonstration sessions, in particular, were conducted on institutional laptops irrespective of the device a participant reported as usual. This analysis therefore concerns self-reported device-preference groups. It does not provide a controlled comparison of acceptance following actual exposure through different devices, and it does not establish equivalent acceptance following mobile and desktop use. Accordingly, no claim of availability across device classes or of equivalent user experience across devices is made anywhere in this paper.

Table 14. Construct means by reported usual or preferred access device, with equivalence testing (secondary exploratory analysis)

Construct	Smartphone (n = 30) M (SD)	Tablet (n = 13) M (SD)	Desktop/Laptop (n = 77) M (SD)	Δ (Mobile Class—Desktop Class)	95% CI	Cohen's d	p (Permutation)	Kruskal–Wallis p	TOST p (δ = 0.5)
PU	3.54 (0.44)	3.54 (0.43)	3.73 (0.55)	–0.193	[–0.366, –0.012]	–0.376	.055	.114	<.001
PEOU	3.54 (0.52)	3.85 (0.53)	3.63 (0.51)	+0.006	[–0.189, +0.199]	+0.012	.956	.185	<.001
IT	3.64 (0.53)	3.94 (0.52)	3.76 (0.67)	–0.029	[–0.249, +0.188]	–0.046	.822	.295	–
PW reduction	3.57 (0.64)	3.67 (0.62)	3.71 (0.70)	–0.111	[–0.353, +0.132]	–0.164	.391	.674	–
CCQ	3.59 (0.68)	3.90 (0.29)	3.61 (0.62)	+0.073	[–0.147, +0.295]	+0.119	.537	.128	–
BI	3.69 (0.48)	3.74 (0.46)	3.64 (0.60)	+0.061	[–0.134, +0.256]	+0.109	.582	.729	<.001
US	3.53 (0.63)	3.75 (0.60)	3.70 (0.66)	–0.104	[–0.340, +0.130]	–0.160	.419	.482	<.001

Notes: Groups are defined by the device each respondent reported as their usual or preferred means of access, not by the device used during the assessed exposure: 30 smartphones, 13 tablets, 51 laptops, and 26 desktop computers. The three leftmost columns report the smartphone and tablet groups as administered, together with the combined desktop class (laptop and desktop computer). Δ, its confidence interval, Cohen's d, the permutation test, and the TOST contrast the mobile class (smartphone and tablet, n = 43) with the desktop class (laptop and desktop computer, n = 77); the Kruskal–Wallis test is computed across the three displayed groups (df = 2). Bootstrap confidence intervals use 10,000 replicates, and the permutation tests use 10,000 relabellings under the seed reported in Supplementary Material S2. None of the six constructs with established compositional invariance differs between the mobile and desktop classes by permutation test or by Kruskal–Wallis test; PU is the borderline case qualified in the text above. TOST finds the two classes equivalent within ±0.5 Likert points for BI, PEOU, and PU. The US row is reported for completeness only: compositional invariance does not hold for that construct (Table 15), so neither its difference nor its equivalence test is interpreted. These are self-reported preference groups; the comparison does not establish equivalent acceptance following actual mobile and desktop use.

Table 15 reports measurement invariance (MICOM, 2,000 permutations) across the mobile and desktop classes defined by the respondent's reported usual or preferred access device. Configural invariance holds by design, and equal means and equal variances hold for all seven constructs. Compositional invariance holds for six of the seven: for US the correlation between the composites built with each group's weights falls below the fifth percentile of its permutation distribution, so compositional invariance is not established for that construct. Partial measurement invariance is therefore established for PU, PEOU, IT, PW Reduction, CCQ, and BI, and the direct comparison of construct scores in Table 14 is warranted for those six but not for US. This is invariance across reported device-preference groups and not across groups exposed to the platform through different devices, and it says nothing about invariance between the real-use and demonstration groups, which was not tested.

Table 15. Measurement invariance across groups defined by reported usual or preferred access device (MICOM, 2,000 permutations)

Construct	c Value	5th Percentile of Null	Compositional Invariance	Equal Means	Equal Variances
PU	0.9810	0.9776	yes	yes	yes
PEOU	0.9909	0.9763	yes	yes	yes
IT	0.9808	0.9672	yes	yes	yes
PW reduction	0.9959	0.9875	yes	yes	yes
CCQ	0.9959	0.9874	yes	yes	yes
BI	0.9965	0.9845	yes	yes	yes
US	0.9939	0.9952	no	yes	yes

Notes: Partial measurement invariance holds for six of the seven constructs across the reported device-preference groups, so the construct scores of those groups can be compared directly for those six. It does not hold for the US, whose group comparison in Table 14 is therefore reported for completeness and is not interpreted. None of this extends to the real-use and demonstration groups, for which measurement invariance was not established.

9 DISCUSSION

Institutional and communication-related antecedents (IT, CCQ) are, in the pooled exploratory model, associated with BI with a magnitude comparable to that of PU, while the direct usability path (PEOU → BI) is statistically inconclusive and the workload-reduction path (PW → BI) is not supported once PU, IT, and CCQ are accounted for. This pattern should not be read as usability being secondary. PEOU has a substantial and statistically supported association with PU—the largest coefficient in the model, and one of the five paths that remain supported in the real-use analysis—and a supported indirect association with BI through PU in the post hoc mediation model of Table 13. Its direct association with BI remains uncertain: the confidence interval includes zero in the pooled model and in the real-use analysis alike, and an interval that includes zero does not establish that a direct association exists. The two-step pattern that is supported here—ease of use operating on intention through usefulness—is consistent with the classical TAM mediation structure [6], [11] and with the e-government and institutional-trust literature in which trust and communication-quality constructs condition the direct ease-of-use effect once usefulness is already explained by ease of use [2], [3].

In the pooled exploratory model, the PW → BI path is not supported. This result, together with the significant total indirect effect through PEOU and PU reported in Table 13, suggests that PW reduction in this sample may operate primarily through PEOU and PU rather than as an independent antecedent of BI. That reading rests on an explicit bootstrapped indirect-effect estimate (0.119, 95% CI [0.050, 0.208], proportion mediated 0.510) rather than on a bivariate correlation. Within the same pooled model, IT shows the same structure in weaker form: alongside its significant direct path, it also carries a total indirect effect whose interval excludes zero (0.064, 95% CI [0.011, 0.144]), so part of its association with intention is routed through ease of use and usefulness. CCQ, by contrast, acts on intention essentially directly (0.065, 95% CI [–0.016, 0.145]). All three are post hoc additions to the hypothesized model and are presented as such, not as confirmed a-priori paths.

The analysis restricted to the 63 real users (refer to Table 12) supports five of the eight paths—PEOU → PU, PW → BI, CCQ → BI, PU → US, and BI → US—and leaves the remaining three inconclusive. PW → BI is supported here and not in the pooled model on an interval that only marginally excludes zero and against a t-test that does not reach significance. The estimate has been re-checked for this revision and independently re-estimated on the same subsample in the R package seminr under both inner weighting schemes it provides; the interval excludes zero in all three implementations, but its lower limit lies close to zero in each of them, and the measurement model of this subsample is weaker than that of the pooled sample, with AVE below 0.50 for PU, PEOU, and BI at n = 63 (Supplementary Material S2). It is therefore reported as a modest, marginal subgroup result and not as a finding of the study. The exploratory comparison between real users and demonstration participants did not detect a statistically significant between-group difference on any path, but measurement invariance was not established across the two exposure groups, and the subgroup sizes limit the sensitivity of that comparison, so it cannot demonstrate equivalence between them. Reduced statistical power at n = 63 is one possible explanation for the paths that lose support in the restricted analysis; a genuine difference between exposure conditions is another, and this design cannot distinguish between them. Claims of acceptance under real institutional use are accordingly limited in this paper to the five paths supported in the restricted analysis, and the pooled model is retained as an exploratory analysis of mixed exposure conditions that should not be generalized directly to experienced institutional users.

9.1 Theoretical contribution

The contribution of this study is a contextual extension of the TAM to a multi-role institutional governance workflow, not a theoretical advance obtained by adding three constructs to the model. IT, PW Reduction, and CCQ are not proposed as new general-purpose TAM antecedents; they are proposed as the contextual specification that a research ethics review workflow imposes on the classical model, in a setting where an applicant, a secretariat, and an evaluating committee interact asymmetrically around a consequential decision. Each construct is bounded accordingly. IT, as operationalized here, is confidence in the platform's data handling and in the accuracy of its recorded actions rather than an undifferentiated trust in the university; the present six-item scale does not fully disentangle trust in the institution, in the committee's judgment, and in the platform's technical safeguards. PW Reduction targets an explicit comparison against the prior manual procedure that the PU items do not ask about, consistent with the low PU–PW HTMT reported in Table 7. CCQ is positioned within the institutional-communication literature [18], [19] and the ethics-review and case-management literatures [20], [26], although its item wording still originates in customer-service scales and is therefore reported as provisional. What this study contributes is evidence on how these context-specific constructs behave in one such workflow, not a claim to have extended acceptance theory itself.

9.2 Moderated claims

In line with the cross-sectional, single-institution, observational design of this study, findings are stated as associations rather than causes: constructs are described as being associated with BI or explaining variance in it, not as driving or causing it.

This study does not establish that institutions should prioritize platform trustworthiness and communication quality over usability investment; it establishes that, in this sample, trust- and communication-related constructs are at least as strongly associated with BI as usefulness, while usability's association is largely indirect. No claim is made about continued adoption over time or about institutional return on investment, since the design is cross-sectional and was not set up to test either.

10 CONCLUSION

This paper proposed and empirically evaluated an extended TAM for a real, in-production Research Ethics Committee Management System at a Peruvian university, incorporating IT, PW reduction, and CCQ alongside the classical PEOU, PU, BI, and US constructs. Because measurement invariance between the two exposure conditions was not established, the substantive conclusions rest on the 63 respondents who used the platform in real institutional activity. In that analysis five structural paths are supported—PEOU → PU, PW → BI, CCQ → BI, PU → US, and BI → US—and the remaining three are inconclusive at this sample size. The pooled model over all 120 responses is reported as an exploratory analysis that combines two exposure conditions: in it, six of the eight hypothesized paths are supported, one (PEOU → BI) is statistically inconclusive, and one (PW → BI) is not supported. The measurement model showed adequate reliability and discriminant validity, with convergent validity satisfied for six of seven constructs and marginally short of the 0.50 threshold for one (PEOU). The platform is an interactive institutional system reachable from several classes of device; the analysis by self-reported usual or preferred access device found no construct-level difference other than a small, borderline one in PU, and it established compositional invariance for six of the seven constructs but not for US, whose group comparison is therefore not interpreted; it is a secondary exploratory analysis of preference groups and is not a controlled comparison of acceptance following exposure through different devices.

Within the real-use analysis, these findings suggest—without implying causation or guaranteed institutional return—that CCQ is positively associated with BI, that PW reduction is marginally and modestly so, on a subgroup interval whose lower limit lies close to zero, that BI and PU are positively associated with US, and that PEOU is positively associated with PU. The associations of PU, IT, and PEOU with BI are supported only in the pooled exploratory model and remain inconclusive among real users.

This study has several limitations beyond those already discussed. First, the sample is heavily weighted toward undergraduate-student applicants and underrepresents internal committee roles, which limits the generalizability of any role-specific conclusion; a larger, role-stratified sample would allow a proper multigroup PLS-SEM comparison. Second, the borderline AVE for PEOU, and the loadings below the 0.708 cutoff, indicate that the measurement instrument for PU and PEOU could be refined in future iterations. Relatedly, the IT, PW Reduction, and CCQ scales were newly contextualized for this platform and have not undergone formal pilot testing or an independent content-validity assessment; their acceptable reliability and convergent-validity statistics in this sample are evidence of internal consistency, not a substitute for content validation. Third, the cross-sectional design captures BI rather than confirmed continued use, and all constructs were measured with one self-report instrument administered on a single occasion, so common-method bias cannot be ruled out by the diagnostic reported in Table 8. Fourth, nearly half the sample experienced the platform through a controlled demonstration rather than real

institutional use; measurement invariance across the two exposure conditions was not established, the exploratory between-group comparison cannot demonstrate that the two groups share the same measurement or structural model, and the pooled estimates should not be read as describing experienced institutional users. Fifth, the device analysis groups respondents by the device they report using habitually rather than by the device through which the evaluated exposure occurred, so it cannot support any conclusion about acceptance following actual use on a given class of device; within that analysis, compositional invariance across the device-preference groups is established for six of the seven constructs but not for US, so the comparison of US between those groups is not interpretable. Future work should re-estimate the model on a larger real-user-only sample, establish measurement invariance before pooling exposure conditions, contrast applicant-role and committee-role subsamples once subgroup sizes allow it, and re-examine the paths left inconclusive under real institutional use—PEOU → BI, PU → BI, and IT → BI—together with PW → BI, whose status differs between the restricted and the pooled analyses.

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