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Article

A Dual-Channel Model of Artificial Intelligence Adoption Intention among Executives of Traditional-Industry SMEs: Perceived Value, Perceived Implementation Risk, and the Boundary Condition of Digital Foundation

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Abstract: Whether a small or medium-sized firm in a traditional industry takes up artificial intelligence is usually settled by the chairman or the general manager alone, without an information-systems department to consult. Existing adoption research draws its evidence mainly from firms that have already completed basic informatisation, so how external conditions reach the executive remains unclear. This study surveyed 526 SME executives in four traditional industries across four Chinese regions and estimated a structural equation model linking technology-side and environment-side conditions, perceived value, perceived implementation risk and adoption intention, with digital foundation as a boundary condition. External conditions split into two mediating pathways, the two channels of the model. Performance expectancy and competitive pressure raise perceived value, while effort expectancy and perceived institutional support leave it unchanged and instead lower perceived implementation risk. Competitive pressure carries opposite signs across the two pathways and its total effect on adoption intention is indistinguishable from zero, as is that of institutional support. Digital foundation weakens the suppression that perceived risk exerts on intention, the slope falling from −0.284 to −0.125, although the two product terms add only 0.007 to the explained variance in intention. Peer demonstration and subsidies do not move these firms, and the estimates locate the reason in a risk they cannot absorb rather than in any shortfall of perceived value; building the data and systems base before the application layer fits the way these firms decide. The design is cross-sectional, so the estimates are associational and the ordering among the constructs rests on theory rather than on temporal precedence.

Keywords: Artificial Intelligence Adoption, SME Executives, Perceived Value, Perceived Implementation Risk, Digital Foundation, Upper Echelons Perspective, Structural Equation Modelling

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1. Introduction

The diffusion of artificial intelligence across firms is markedly uneven. The OECD (2021) assessment of SME digitalisation among member economies reports that the smaller the firm and the more traditional its industry, the lower its take-up of advanced digital technologies, with the gap against large firms widening at the level of artificial intelligence. The bibliometric account of digital transformation research by Kraus et al. (2021) shows empirical evidence concentrated in firms that have already completed

basic informatisation; Wamba-Taguimdje et al. (2020) trace the business value of AI transformation projects to process automation, decision support and customer interaction, all three of which presuppose existing data and systems. The tests of AI adoption in manufacturing and production firms by Chatterjee et al. (2021) and the analysis of AI-based B2B practices among SMEs by Baabdullah et al. (2021) both restrict observation to firms with some informatisation already in place, which excludes by construction the traditional firms whose production data have never been digitised. Cubric (2020) assembles drivers, barriers and social considerations for AI in business and management in a tertiary study, listing skill shortages and weak organisational implementation capacity among the main barriers; Dwivedi et al. (2021) place SME access to artificial intelligence on the multidisciplinary agenda as an open question.

The decision structure of traditional-industry SMEs differs in substance from these samples. Such firms have no separate information-systems department, no formal technology review procedure, and no diversified business lines over which the cost of experimentation can be spread. Whether a technology is taken up is decided by the chairman, the general manager or a single functional executive, typically without internal expert advice. The upper echelons perspective of Hambrick and Mason (1984) treats organisational behaviour as a reflection of the cognition and values of top managers, and that reflection is far stronger in SMEs than in bureaucratised large firms. Liang et al. (2007) test the effect of institutional pressures on enterprise system assimilation and conclude that external pressure has to pass through the attention allocation of top management before it becomes organisational action, with the top-management stage carrying the greater part of the mediation. Moving the unit of analysis from "the firm" down to "the adoption intention of the individual executive" is not a simplification in the SME setting; it locates the study where the decision is actually made.

Individual-level frameworks such as the technology acceptance model (Davis, 1989) and the unified theory of acceptance and use of technology (Venkatesh et al., 2003) attribute adoption intention to performance expectancy and effort expectancy. Organisational-level frameworks such as the technology–organization–environment (TOE) framework (Tornatzky & Fleischer, 1990) and diffusion of innovations theory (Rogers, 2003) attribute adoption to technological attributes, organisational conditions and environmental pressure. The comparison by Oliveira and Martins (2011) identifies what each family omits. Individual-level frameworks leave out environmental variables and organisational-level frameworks leave out the cognitive processing stage. The joint between them lies in how external conditions are translated by the decision maker into subjective assessments. Kim et al. (2007) place benefit perceptions and sacrifice perceptions inside a single construct of perceived value, which absorbs all antecedents; Featherman and Pavlou (2003) decompose perceived risk into performance, financial and privacy components and conclude that risk and benefit act on adoption intention independently rather than as two ends of one dimension. Read together, the two lines suggest that external conditions may not reach adoption intention through a single pathway but split into two parallel assessments of value and of risk that can work against each other. A further stream explains why firms hold back even when they judge a technology worthwhile. Cenfetelli (2004) separates inhibitors from enablers of system usage and shows that the two are not opposite ends of one scale, so what suppresses adoption need not be the absence of what promotes it. Polites and Karahanna (2012) trace the hold of incumbent habit, switching cost and inertia on the acceptance of a new system, and Kim and Kankanhalli (2009) attribute user resistance to status quo bias rather than to a low estimate of benefit. At the organisational level, Piderit (2000) and Ashforth et al. (2014) argue that attitudes towards change are routinely ambivalent, the positive and the negative component being held at the same time, while Talke and Heidenreich (2014) and Claudy et al. (2015) show that decision models which omit the resistance side overstate adoption. This literature is the reason for keeping the risk assessment as a construct of its own rather than treating it as the negative tail of perceived value.

This split takes a testable form in traditional-industry SMEs. Local subsidies for intelligent upgrading, matchmaking events run by industrial parks and demonstration by competitors are all designed to raise adoption intention; if these same conditions raise the executive's fear of implementation failure, the net effect need not be positive. Gan and Xiao (2025), analysing how generative AI reconstructs the innovation systems of SMEs, argue that algorithm-participative knowledge creation lands only where the firm already holds data an algorithm can read. Gan et al. (2026), in a systematic review of anxiety, resistance and governance transformation among low-skilled workers under artificial intelligence, note that the internal organisational resistance triggered by technology entry has long stayed outside the field of view of adoption research. Yue et al. (2026) treat technology anxiety as a boundary variable in fresh-food e-commerce and test its effect on the link between perceived service quality and continuance intention. Together these results point to a proposition that has not been tested directly in SME artificial intelligence research: a firm's own digital condition is not only a precondition for adoption but may also change how hard risk perception presses on intention.

Three questions follow. Does each of the four technology-side and environment-side antecedents reach adoption intention through perceived value or through perceived implementation risk? Do the two pathways point the same way, or do they cancel? And what boundary role does a firm's digital foundation play between risk perception and intention?

The contribution is bounded deliberately. This study does not propose a new theory of adoption. It takes constructs already established in the technology acceptance, technology–organization–environment and perceived risk literatures and specifies where

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each of them acts once the decision maker is a single executive in a firm with no information-systems function. Three increments follow: a common set of antecedents is split into a value assessment and a risk assessment estimated within one model; two environment-side antecedents are shown to produce total effects near zero because the two pathways carry opposite signs; and the firm's digital foundation is identified as a boundary condition that operates on the risk pathway alone. Statements marked as hypotheses are propositions derived from that literature, the coefficients reported in Section 4 are the evidence bearing on them, and the two are kept apart throughout. One term is fixed here: the model as a whole is called dual-channel, and the two mediating routes it specifies, through perceived value and through perceived implementation risk, are called pathways.

2. Theoretical Background and Hypothesis Development

2.1. Bridging the TOE Framework and the Upper Echelons Perspective

The technology–organization–environment framework sorts the determinants of an adoption decision into three domains (Tornatzky & Fleischer, 1990). Zhu and Kraemer (2005) test the framework on cross-country retail data, where the positive effect of competitive pressure on the depth of e-business use holds; Lin (2014) works with manufacturing firms and finds effects from all three domains on electronic supply chain management system adoption. What the framework explains is organisational behaviour, and the stage at which the decision maker processes these conditions is absent. The unified theory of acceptance and use of technology supplies that stage by setting performance expectancy and effort expectancy as direct antecedents (Venkatesh et al., 2003), and Venkatesh et al. (2012) bring price value and hedonic motivation into the consumer version, writing the trade-off between benefit and sacrifice formally into the model.

The upper echelons perspective supplies the missing stage in a form specific to this setting. Hambrick and Mason (1984) hold that organisational outcomes reflect the cognitive base and the values of the dominant coalition, whose members act not on the objective situation but on a construed reality filtered through a limited field of vision, selective perception and interpretation. Hambrick (2007) states the condition under which that filtering matters most, namely managerial discretion, which is greatest where the situation is unstructured, the firm small and the decision concentrated in few hands (Hambrick & Finkelstein, 1987). An SME in a traditional industry facing an artificial intelligence decision meets all three conditions at once. Ocasio (1997) and Liang et al. (2007) supply the mechanism: an external condition becomes organisational action only after it captures the attention of top management, so the executive stage decides the effect of an environmental variable rather than merely relaying it. The perspective is put to work here in three specific places. It fixes the level of analysis at the individual executive rather than the firm. It identifies perceived value and perceived implementation risk as the interpretation stage through which the technology and environment domains must pass, so that the two constructs are not free-standing mediators but the content of the executive's construed reality. And it treats executive age and education as observable proxies for the cognitive base, whose coefficients are reported and read in Section 5.3 rather than absorbed silently as controls.

For an SME executive, conditions in the technology and environment domains are externally given information inputs; perceived value and perceived implementation risk are the outputs after processing; adoption intention is the behavioural tendency that follows. The four antecedents are defined as follows. Performance expectancy is the executive's estimate of how far operating indicators would improve after artificial intelligence is introduced, following Venkatesh et al. (2003) and Chatterjee et al. (2021). Effort expectancy is the executive's estimate of the learning cost and the volume of process rework the firm would have to absorb. Competitive pressure is the perceived requirement to keep up technologically, coming from competitors and downstream customers, defined after Zhu and Kraemer (2005). Perceived institutional support is the perceived availability of resources from local government, public service platforms and industry bodies, drawing on the distinction Liang et al. (2007) and Bag et al. (2021) make between the normative and the supportive components of institutional pressure.

The two intermediate constructs follow the value–risk pairing. Perceived value is the executive's net benefit judgement after weighing inputs against outputs (Kim et al., 2007; Zeithaml, 1988). Perceived implementation risk is the subjective estimate of the likelihood of sunk expenditure, data leakage, absence of qualified personnel and disruption of production order during introduction (Featherman & Pavlou, 2003). Digital foundation is the firm's existing degree of data digitisation, information system usage, system maintenance manpower and cross-departmental data accessibility, defined with reference to the firm-level AI readiness of Alsheibani et al. (2018) and the AI capability measure of Mikalef and Gupta (2021).

The four bodies of work enter the model in distinct roles rather than side by side. The technology–organization–environment framework settles which external conditions are admitted; the upper echelons and attention-based arguments settle who processes them and why that stage is decisive in an SME; the unified theory of acceptance and use of technology settles the evaluative dimensions on which the processing runs; and the value–risk pairing settles the form of the output, two assessments rather than one. The

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chain runs in a single direction: external conditions, processing by one executive, two assessments, intention. Each construct occupies one position in that chain and is measured at the level that position implies, which is what separates an integrated specification from a list of frameworks assembled for coverage.

2.2. Splitting the Technology-Side Antecedents

Performance expectancy describes the benefit end. An executive who expects artificial intelligence to shorten delivery cycles, cut unit labour cost and reduce rework enters that expectation directly on the credit side of the net benefit calculation. Chatterjee et al. (2021) in manufacturing and production firms and Pillai and Sivathanu (2020) in human resource management both test the effect of perceived usefulness on AI adoption intention, and in each model the estimate reaches statistical significance and ranks among the leading antecedents. Performance expectancy also carries an implicit judgement about technological maturity: an executive who believes the technology delivers a definite improvement worries less about implementation failure. That negative link should be weaker than the positive link to the value side, since performance expectations answer whether benefits will arrive and say little about whether the process will go wrong.

Hypothesis 1 (H1a): Performance expectancy positively predicts perceived value.

Hypothesis 1 (H1b): Performance expectancy negatively predicts perceived implementation risk.

Effort expectancy describes the process end. Executives of traditional-industry SMEs are rarely the ones operating the system. Their judgement of how easy a tool is to use converts poorly into any figure on the profit and loss account, yet it maps directly onto worries of the form “the staff will not take it up after go-live” and “there will be nobody to maintain it”. Davis (1989) reports in the original test that the effect of perceived ease of use on usage runs largely through perceived usefulness, its direct link being the weaker of the two; the AI project value sources traced by Wamba-Taguimdje et al. (2020) likewise sit at the process and decision level rather than at ease of operation. Transposed to an executive sample, effort expectancy should link weakly to the value end and strongly to the risk end.

Hypothesis 2 (H2a): Effort expectancy positively predicts perceived value.

Hypothesis 2 (H2b): Effort expectancy negatively predicts perceived implementation risk.

2.3. The Double-Edged Form of the Environment-Side Antecedents

Competitive pressure has long been treated in adoption research as a one-directional driver. The mimetic isomorphism of DiMaggio and Powell (1983) supplies the source of that drive: when outcomes are uncertain, organisations copy what their peers do. The empirical results of Zhu and Kraemer (2005), Lin (2014) and Sun et al. (2020) all support a positive effect of competitive pressure on adoption. For an SME this drive carries a by-product: a competitor’s earlier move compresses the firm’s own decision window. Compression is itself a source of risk, since following without adequate assessment raises the chance of sunk expenditure and of disruption to the production order. The barriers to AI adoption that Kar and Kushwaha (2023) extract from public opinion text include insufficient implementation capability and expected project failure, and both are amplified under pressure to keep up. Competitive pressure therefore takes a double-edged form: it raises the value judgement and the risk judgement together.

Hypothesis 3 (H3a): Competitive pressure positively predicts perceived value.

Hypothesis 3 (H3b): Competitive pressure positively predicts perceived implementation risk.

Perceived institutional support works the other way round. Local fiscal funds, technical guidance from public service platforms and matchmaking run by industrial parks change the fallback conditions surrounding implementation, not what the technology itself can earn for the firm. A subsidy reduces the severity of sunk expenditure and platform guidance eases the shortage of personnel; neither changes the executive’s answer to the question of what the technology will do for orders and costs. Bag et al. (2021) separate institutional pressures from resources as two sets of antecedents of big-data-powered AI adoption, locating the contribution of the resource side in the firm’s implementation capability and that of the pressure side in internal organisational conditions. Read against the three pillars of Scott (2014), the construct sits on the regulative pillar, where rules, funds and monitoring set the conditions of compliance, and on the supportive part of the normative pillar carried by trade associations and industrial parks; the cultural-cognitive pillar, which governs what counts as a taken-for-granted way of running a firm, is not measured here. Oliver (1991) adds that organisations respond to institutional processes strategically, from acquiescence through to avoidance, and that the response turns

on the resources the organisation holds, which is consistent with support acting on the capacity to bear failure rather than on the earnings the technology promises. One consequence follows for interpretation. The content of the construct, that is, application-based subsidies, public service platforms, park matchmaking and an explicit policy category for intelligent upgrading, belongs to the Chinese institutional environment described by Peng et al. (2008), so the estimate reported below is the effect of that particular support package rather than of institutional support in general; Section 5.6 returns to what this implies elsewhere.

Hypothesis 4 (H4a): Perceived institutional support positively predicts perceived value.

Hypothesis 4 (H4b): Perceived institutional support negatively predicts perceived implementation risk.

2.4. From the Two Pathways to Adoption Intention

Perceived value is the composite net benefit judgement, and its link to adoption intention has been tested repeatedly in value-based adoption models. The value-based adoption model of Kim et al. (2007) makes perceived value the sole direct antecedent of adoption intention, with benefit and sacrifice components netted out inside the value construct before they act on intention. Perceived implementation risk describes the expectation of adverse consequences during introduction, and its suppressive effect on intention holds in e-service adoption (Featherman & Pavlou, 2003) and in artificial intelligence adoption (Cubric, 2020). The two pathways are conceptually independent: a firm can hold that artificial intelligence is worth the money and at the same time doubt that it can pull the project off. That combination is what the organisational literature calls ambivalence, a positive and a negative evaluation of the same object held together rather than netted into one position (Ashforth et al., 2014; Piderit, 2000). Forcing the two assessments onto one dimension pushes the ambivalent case towards a middle score that misrepresents both components, which is the specification tested as M3 and rejected in Section 4.6.

Hypothesis 5 (H5): Perceived value positively predicts adoption intention.

Hypothesis 6 (H6): Perceived implementation risk negatively predicts adoption intention.

Four antecedents mediated through two pathways give eight indirect effects. The form of each antecedent's net effect depends on how the signs combine across the two pathways: performance expectancy and effort expectancy act in the same direction on both pathways by raising value and lowering risk, competitive pressure raises value and raises risk at once, and perceived institutional support works mainly through the risk pathway.

Hypothesis 7 (H7a–H7d): The effects of performance expectancy, effort expectancy, competitive pressure and perceived institutional support on adoption intention are mediated by perceived value.

Hypothesis 8 (H8a–H8d): The effects of performance expectancy, effort expectancy, competitive pressure and perceived institutional support on adoption intention are mediated by perceived implementation risk.

2.5. Digital Foundation as a Boundary Condition

Digital foundation carries two identities in artificial intelligence adoption. As a precondition, machine-readable data stock, an information system already running and staff able to maintain it constitute the feasibility base for introduction. Alsheibani et al. (2018) group such conditions under firm-level AI readiness; the AI capability instrument of Mikalef and Gupta (2021) covers tangible resources, human skills and intangible organisational elements, and its positive effect on organisational creativity and firm performance holds in their firm sample. Xiao and Gan (2026), in an integrative review of operations reconfiguration under big data, argue that the conversion from data possession to operations reconfiguration depends on internal data accessibility rather than on data volume. This identity corresponds to a direct effect of digital foundation on adoption intention.

The second identity is that of a buffer on risk perception. Perceived implementation risk has specific content: a system that never goes live, no one available to maintain it, disruption of the production order. Firms already running ERP or MES, already staffing system maintenance and already able to move data across departments absorb part of that content through conditions they hold. The technology readiness index of Parasuraman (2000) sets optimism and innovativeness as contributor dimensions and discomfort and insecurity as inhibitor dimensions, the four jointly governing how an individual responds to new technology. Yue et al. (2026) test the boundary role of technology anxiety on the link between perceived service quality and continuance intention in fresh-food e-commerce, providing consumer-side evidence that the strength of an inhibitory psychological variable varies with external conditions. On the firm side, the higher the digital foundation, the weaker the suppression that risk perception exerts on adoption intention. Whether digital foundation amplifies the value pathway in the same way has no corresponding theoretical basis: a net

benefit judgement is formed from market and cost information and has no direct correspondence with the firm's internal system conditions. That statement is offered as a contrast hypothesis.

Hypothesis 9 (H9): Digital foundation positively predicts adoption intention.

Hypothesis 10 (H10): Digital foundation weakens the negative effect of perceived implementation risk on adoption intention.

Hypothesis 11 (H11): Digital foundation strengthens the positive effect of perceived value on adoption intention.

The research model is shown in Figure 1.

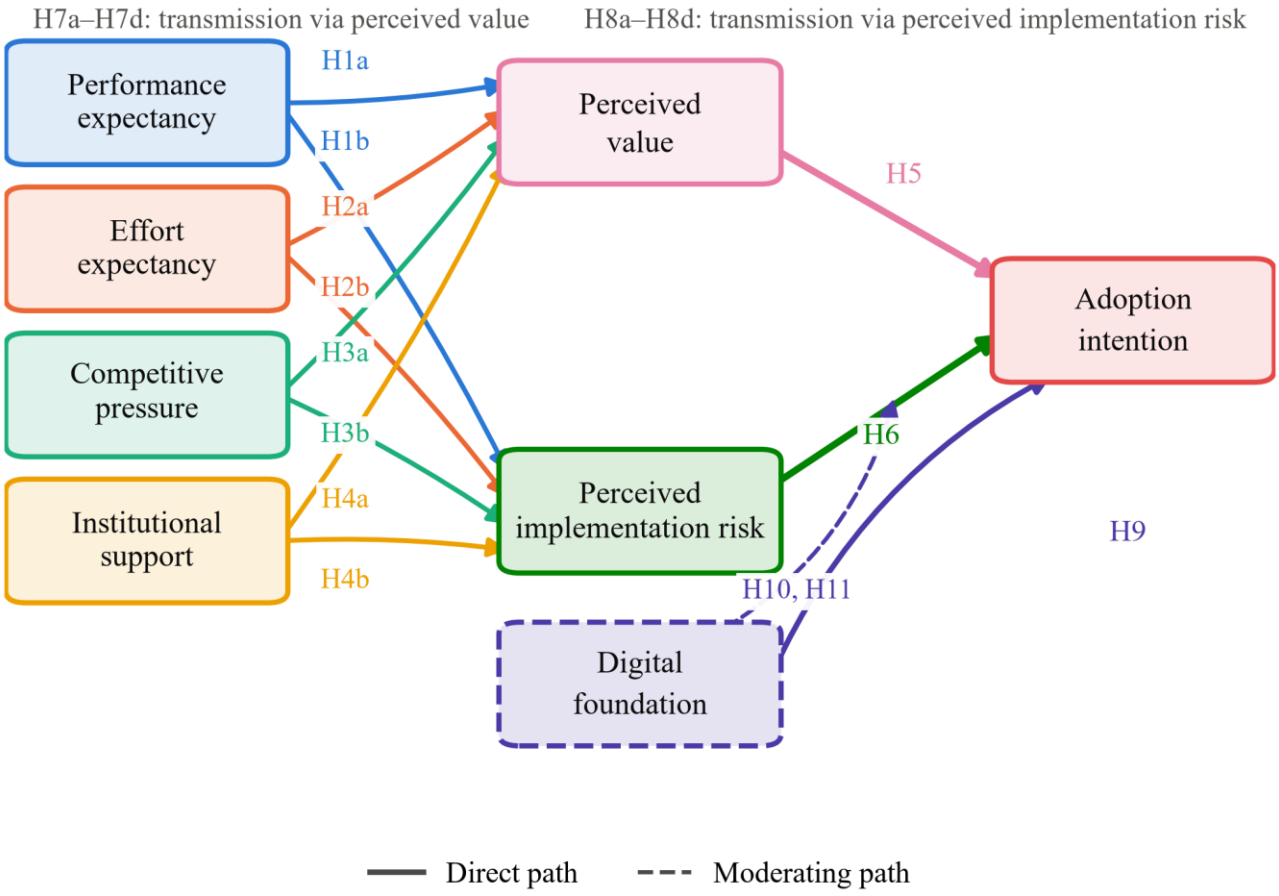


Figure 1. Research model. Source: Authors.

3. Materials and Methods

3.1. Sampling and Data Collection

The sampling frame was restricted to four traditional industries: manufacturing in textiles and apparel, food processing, metal products and furniture and building materials; wholesale and retail; transport, warehousing and postal services; and construction and installation. Firms were screened to 20–300 employees, corresponding to the small and medium bands of the relevant industries under the Provisions on the Standards for Classifying Small and Medium-sized Enterprises issued as MIIT Joint Enterprise [2011] No. 300, excluding micro firms below 20 employees and large firms above 300. Coverage spans the Yangtze River Delta, the Pearl River Delta, the Chengdu–Chongqing area and the central provinces of Henan, Anhui, Hunan and Hubei, taking in regional differences in digital infrastructure and industrial structure.

Questionnaires were distributed through three routes: membership rosters of local federations of industry and commerce and trade associations, enterprise service desks in industrial parks across the four areas, and referrals from firms the research team had worked with previously. Respondents were restricted to the chairman, general manager, deputy general manager, or the executive in charge of informatisation or production, with one valid questionnaire accepted per firm. Between September and December 2025, 680 questionnaires were distributed and 592 returned, a return rate of 87.06%. Three exclusion rules applied: identical responses across all items of a scale; completion time below 180 seconds; firm size or industry outside the sampling frame. The final set

comprises 526 valid questionnaires, an effective rate of 77.35%. Sixty-six of the 592 returns were removed under these rules. The three distribution routes yield a purposive rather than a probability sample: the frame consists of firms reachable through business associations, park service desks and prior working contacts, which is stated here because it bounds the population to which the estimates apply. Table 1 lists every item, Section 3.3 states the estimation and inference rules applied to them, and Section 3.4 names the software that produced each result, so that the chain from questionnaire to reported coefficient can be followed at each step.

Nonresponse bias was checked following Armstrong and Overton (1977). The sample was split by return date into an early group of 333 and a late group of 193, and independent-samples t tests on the composite scores of the eight constructs returned t values between −0.940 and 0.295 with p-values between .348 and .939, so the two groups do not differ at the .05 level.

3.2. Measures

All eight constructs use established scales in adapted form, four items each, answered on a seven-point Likert scale running from 1 for strongly disagree to 7 for strongly agree. English source scales were processed through the back-translation procedure of Brislin (1970): two management doctoral researchers translated into Chinese independently, a third bilingual researcher with no access to the original translated back into English, and wording differences against the source scale were resolved in revision. The revised draft went to six executives of traditional-industry SMEs for cognitive interviews, in which expressions such as “organisational agility” and “data assets” were replaced by wording the respondents use themselves, and three information-systems scholars then reviewed content validity. Items and sources appear in Table 1.

Table 1. Measurement items and sources.

Construct	Code	Item	Source
Performance expectancy	PE1	Introducing AI would shorten our order delivery cycle	Venkatesh et al. (2003) Chatterjee et al. (2021)
	PE2	Introducing AI would lower our unit labour cost	
	PE3	Introducing AI would reduce quality defects and rework	
	PE4	Introducing AI would improve the accuracy of our reading of market demand	
Effort expectancy	EE1	Our staff would not need long to learn to use AI tools	Davis (1989) Venkatesh et al. (2003)
	EE2	The interfaces of available AI products are clear to our frontline staff	
	EE3	Fitting AI tools into our existing processes would not take a great deal of extra work	
	EE4	Vendor training would be enough for us to run these tools ourselves	
Competitive pressure	CP1	Our main competitors already use AI-related tools	Zhu & Kraemer (2005) Lin (2014)
	CP2	Not introducing AI would put us at a disadvantage on price quotations	
	CP3	Downstream customers have begun screening suppliers by intelligent capability	
	CP4	The pace of competition in our industry forces us to decide on technology quickly	
Perceived institutional support	IS1	Local government provides funds our firm can apply for towards intelligent upgrading	Liang et al. (2007) Bag et al. (2021)
	IS2	Public service platforms can give us technical guidance on AI applications	
	IS3	Trade associations or industrial parks have organised AI-related matchmaking events	
	IS4	Current policy explicitly covers intelligent upgrading for firms such as ours	

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Perceived value	PV1	Weighing inputs against outputs, introducing AI is worthwhile for our firm	Zeithaml (1988) Kim et al. (2007)
	PV2	The returns AI brings exceed what we would pay for it	
	PV3	Compared with other technology investments open to us, AI offers the better return	
	PV4	Given how our business currently stands, this expenditure is justified	
Perceived implementation risk	PR1	We worry that the system will never go into real use after the money is spent	Featherman & Pavlou (2003) Cubric (2020)
	PR2	We worry that business data will leak or be misused in the course of use	
	PR3	We worry that no one will be able to maintain a system of this kind	
	PR4	We worry that the introduction process will disrupt existing production or operations	
Digital foundation	DF1	Our production or operating data are already recorded electronically	Alsheibani et al. (2018) Mikalef & Gupta (2021)
	DF2	We already run ERP, MES or a comparable information system	
	DF3	We have staff assigned to day-to-day maintenance of information systems	
	DF4	Data can be accessed across departments in our firm	
Adoption intention	ADI1	We intend to introduce AI-related applications within the next 12 months	Venkatesh et al. (2012) Baabdullah et al. (2021)
	ADI2	We are willing to set aside a dedicated budget for AI applications	
	ADI3	Where conditions allow, we would give priority to AI-type technical upgrading	
	ADI4	We would recommend introducing AI applications to firms in our industry	

Source: Authors, adapted from the published scales cited in the final column.

Five control variables were recorded: firm size in three employee bands, firm age in four bands, executive age in four bands, executive education in four bands, and industry coded 1 for manufacturing and 0 otherwise. Firm size and firm age enter the perceived value equation, firm size and executive age enter the perceived implementation risk equation, and all five enter the adoption intention equation.

3.3. Procedural Control of Common Method Bias and Analytical Strategy

Self-reported data from a single source carry a risk of method variance. Four procedural controls follow Podsakoff et al. (2003): the questionnaire carries no statement of the research topic or hypothesised directions; antecedents, intermediate variables and the outcome variable sit in separate blocks with unrelated filler items between them; a reverse-worded attention check appears in the perceived implementation risk scale; and respondents received a written undertaking of anonymity and of statistical use only.

Analysis follows the two-step procedure of Anderson and Gerbing (1988): the measurement model is tested by eight-factor confirmatory factor analysis, and the structural model is estimated once it passes. Parameters are estimated by maximum likelihood. Fit is evaluated against the criteria of Hu and Bentler (1999): $\chi^2/df < 3$, CFI and TLI ≥ 0.90, RMSEA ≤ 0.08, SRMR ≤ 0.08. Indirect effects are tested with 5,000 bias-corrected bootstrap resamples, judged by whether the 95% confidence interval excludes zero (Preacher & Hayes, 2008); the full measurement and structural model is re-estimated on every resample, which avoids the understatement that comes from resampling point estimates alone. Moderation follows Aiken and West (1991), standardising the variables before forming the product terms, and is judged by the ΔR^2 of a hierarchical regression and by the interaction coefficients, with simple slopes computed at ±1 standard deviation; product-indicator estimation of latent interactions is more sensitive to sample size

and distributional assumptions (Marsh et al., 2004) and was not adopted as the main approach. Moderated mediation is tested with the index method of Hayes (2015). Group differences in path coefficients are tested with the *z* statistic for the equality of regression coefficients given by Paternoster et al. (1998). Two decision rules are fixed in advance and applied throughout. All tests are two-tailed and evaluated at the .05 level. A directional hypothesis counts as supported when the estimate carries the hypothesised sign and reaches that level, whatever its magnitude; an estimate that reaches the level but is small in size is flagged as small in the text rather than reclassified as a failure.

3.4. Software and the Use of Generative Artificial Intelligence

Estimation was carried out in two packages, and the division between them is stated so that each reported figure can be traced to its source. IBM SPSS Statistics produced the descriptive statistics, the reliability coefficients, the three common method tests, the hierarchical regressions, the simple slopes and the group comparison. IBM SPSS Amos produced the confirmatory factor analysis, the structural model, the four competing models and the 5,000 bias-corrected bootstrap resamples on which the indirect effects and the moderated mediation indices rest; the full measurement and structural model is re-estimated on every resample. Every figure reported below was drawn from the numerical output of those two packages, and the output files, the syntax and the questionnaire data are available from the corresponding author.

Generative artificial intelligence was used at one point in the preparation of this manuscript and at no other: to polish the English wording of passages the authors had already written in full. It was not used to design the study, to construct or translate the scales, to generate, impute or clean any part of the survey data, to write or execute analysis code, to compute any estimate, to produce any figure or table, or to draft the argument of any section. The dataset described in Section 3.1 consists of questionnaires completed by the 526 executives within the sampling frame and comes from no other source. Each polished sentence was checked against the authors' original wording before it was accepted, and the authors take full responsibility for every statement in the manuscript.

4. Results

4.1. Sample Profile

The distribution of the 526 sampled firms appears in Table 2. Manufacturing accounts for 44.68%, matching the industry weights in the sampling frame. Firms with 20–49 employees make up 39.92%, those with 50–99 employees 38.59% and those with 100–300 employees 21.48%, so the sample sits towards the smaller end. Firms trading for more than ten years total 58.55%, most of them past the start-up stage. Among the responding executives, 59.12% are aged 45 or over, 54.76% hold a bachelor's degree or above, and 36.12% are the chairman or general manager in person.

Table 2. Profile of the 526 sampled firms and their responding executives.

Category	Group	*n*	%	Category	Group	*n*	%
Industry	Manufacturing	235	44.68	Executive age	Under 35	45	8.56
	Wholesale and retail	122	23.19		35–44	170	32.32
	Transport and warehousing	96	18.25		45–54	183	34.79
	Construction and installation	73	13.88		55 and above	128	24.33
Employees	20–49	210	39.92	Executive education	High school or below	89	16.92
	50–99	203	38.59		Junior college	149	28.33
	100–300	113	21.48		Bachelor's degree	229	43.54
Firm age	Under 5 years	61	11.60		Master's or above	59	11.22
	5–9 years	157	29.85	Position	Chairman/general manager	190	36.12
	10–19 years	191	36.31		Deputy general manager	189	35.93
	20 years and above	117	22.24		Executive for IT/production	147	27.95
Region	Yangtze River Delta	179	34.03				

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Pearl River Delta	138	26.24
Chengdu–Chongqing	116	22.05
Central China	93	17.68

Source: Authors.

The same distributions are shown graphically in Figures A1 and A2 in Appendix A. Manufacturing is the largest single industry, the weight of the sample lies below 50 employees, executives aged 45 and over make up close to six in ten of the respondents, and the four regions differ in sample size by less than twenty percentage points.

4.2. Reliability and Convergent Validity

Skewness across the 32 items runs from −0.321 to 0.129 and kurtosis from −0.648 to −0.142, inside the |skewness| < 2 and |kurtosis| < 7 range, so the normality premise of maximum likelihood estimation holds. The eight-factor confirmatory factor analysis returns $\chi^2 = 689.97$, $df = 436$, $\chi^2/df = 1.583$, CFI = 0.973, TLI = 0.969, GFI = 0.929, AGFI = 0.920, RMSEA = 0.033 and SRMR = 0.036, each better than the criteria of Hu and Bentler (1999).

Reliability and convergent validity appear in Table 3. Cronbach's α runs from 0.846 to 0.892 and composite reliability from 0.845 to 0.891, both above the 0.70 threshold (Bagozzi & Yi, 1988). Standardised loadings run from 0.668 to 0.907, with only DF4 falling between 0.60 and 0.70; following the treatment rule of Hair et al. (2019), an item with a loading in that band is retained where the composite reliability and average variance extracted of its construct both meet their thresholds. Average variance extracted runs from 0.578 to 0.674, all above 0.50 (Fornell & Larcker, 1981). Two qualifications belong beside these figures. DF4, on cross-departmental data accessibility, is retained on two grounds: its construct meets both thresholds with the item in place, at CR = 0.854 and AVE = 0.596, and accessibility across departments is the facet of digital foundation that carries the mechanism tested in this study, so dropping the item would raise the average loading at the cost of the content the construct is meant to cover. The average variance extracted of digital foundation, 0.596, and of effort expectancy, 0.578, clear the 0.50 threshold but not by a wide margin, so these two constructs carry more measurement error than the other six and every estimate involving them is correspondingly less precise; the point is taken up again among the limitations in Section 6.

Table 3. Reliability and convergent validity.

Construct	Items	Loading Range	Cronbach's α	CR	AVE	*M*	*SD*
Performance expectancy	4	0.777–0.822	0.873	0.873	0.632	5.061	0.955
Effort expectancy	4	0.718–0.815	0.846	0.845	0.578	4.572	1.018
Competitive pressure	4	0.777–0.803	0.870	0.870	0.626	5.271	0.917
Perceived institutional support	4	0.747–0.798	0.856	0.857	0.600	4.396	1.065
Perceived value	4	0.736–0.907	0.892	0.891	0.674	4.858	1.007
Perceived implementation risk	4	0.750–0.876	0.877	0.876	0.640	5.002	1.028
Digital foundation	4	0.668–0.862	0.855	0.854	0.596	3.947	1.089
Adoption intention	4	0.702–0.858	0.876	0.876	0.639	4.695	1.043

Source: Authors.

The distribution of the 32 loadings appears in Figure 2. All but DF4 at 0.668 sit above the 0.70 reference line. PV1 at 0.907 in perceived value and PR2 at 0.876 in perceived implementation risk are the two highest in the table, and the widest within-construct spread of 0.194 occurs in digital foundation, so no construct rests on a single item.

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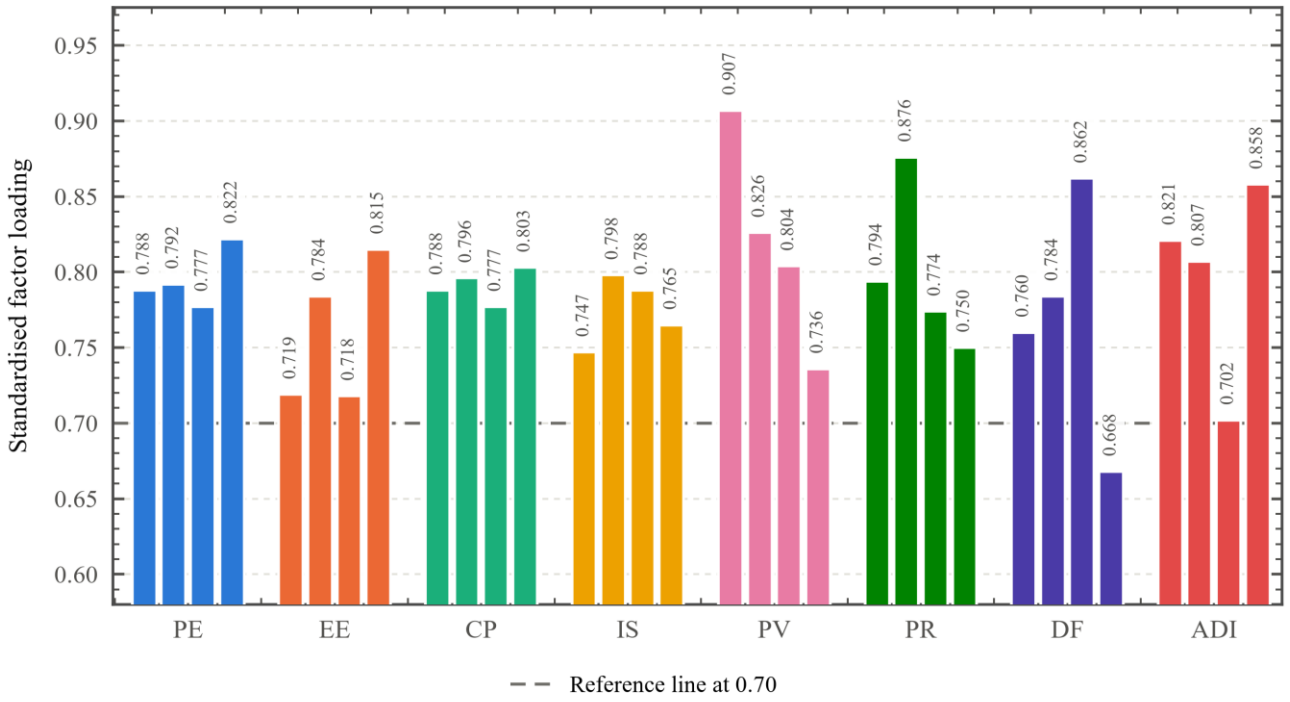


Figure 2. Standardised factor loadings by construct. Source: Authors.

Two figures in the descriptive statistics deserve separate mention. Digital foundation has a mean of 3.947 and is the only one of the eight constructs below the scale midpoint of 4; its standard deviation of 1.089 is also the largest. The sampled firms are therefore weak on data digitisation, running systems and maintenance manpower, and they differ widely among themselves. Perceived implementation risk has a mean of 5.002 against 4.858 for perceived value, so these executives estimate the adverse consequences of the introduction process more strongly than they estimate the net benefit.

Score distributions for the eight constructs appear in Figure A3 in Appendix A. Digital foundation is the only construct on which more than a quarter of the sample scores 3 or below, with an interquartile range of 1.50 straddling the scale midpoint; competitive pressure lies wholly above 4.5 with its upper tail against the scale ceiling; and the distributions of perceived implementation risk and adoption intention are close to symmetric about medians of 5.00 and 4.75.

4.3. Discriminant Validity

Discriminant validity was tested against two standards, with results in Table 4. The square roots of AVE on the diagonal run from 0.760 to 0.821, each exceeding the latent correlations in its row and column; the closest pair is perceived value and adoption intention at $r = 0.625$, against square roots of AVE of 0.821 and 0.799. The maximum heterotrait–monotrait ratio is 0.589, for perceived value and adoption intention, below the strict 0.85 threshold (Henseler et al., 2015). Variance inflation factors for the eight constructs run from 1.208 to 1.452, far below 5, so multicollinearity does not obstruct estimation.

Table 4. Latent correlations and discriminant validity.

Construct	1	2	3	4	5	6	7	8
1 Performance expectancy	**0.795**	0.337	0.399	0.312	0.543	−0.215	0.390	0.515
2 Effort expectancy	0.287	**0.760**	0.239	0.276	0.276	−0.436	0.576	0.405
3 Competitive pressure	0.342	0.206	**0.791**	0.466	0.509	−0.014	0.241	0.315
4 Perceived institutional support	0.268	0.232	0.403	**0.775**	0.339	−0.205	0.311	0.294
5 Perceived value	0.447	0.239	0.442	0.288	**0.821**	−0.054	0.294	0.625
6 Perceived implementation risk	−0.184	−0.363	−0.009	−0.176	−0.033	**0.800**	−0.309	−0.359
7 Digital foundation	0.338	0.459	0.203	0.259	0.243	−0.244	**0.772**	0.437
8 Adoption intention	0.439	0.336	0.268	0.252	0.521	−0.317	0.377	**0.799**

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Note: The diagonal in bold gives the square root of AVE, the lower triangle gives Pearson correlations among composite scores, and the upper triangle gives the latent correlations from the confirmatory factor analysis. Source: Authors.

Apart from competitive pressure with perceived implementation risk ($r = -0.009$, $p = .834$) and perceived value with perceived implementation risk ($r = -0.033$, $p = .451$), all correlations have p-values below .05. The overall shape of the correlation structure appears in Figure 3: perceived implementation risk is the only construct linked negatively to the other seven, its links with competitive pressure and perceived value sit near zero, and its strongest negative link is with effort expectancy ($r = -0.363$).

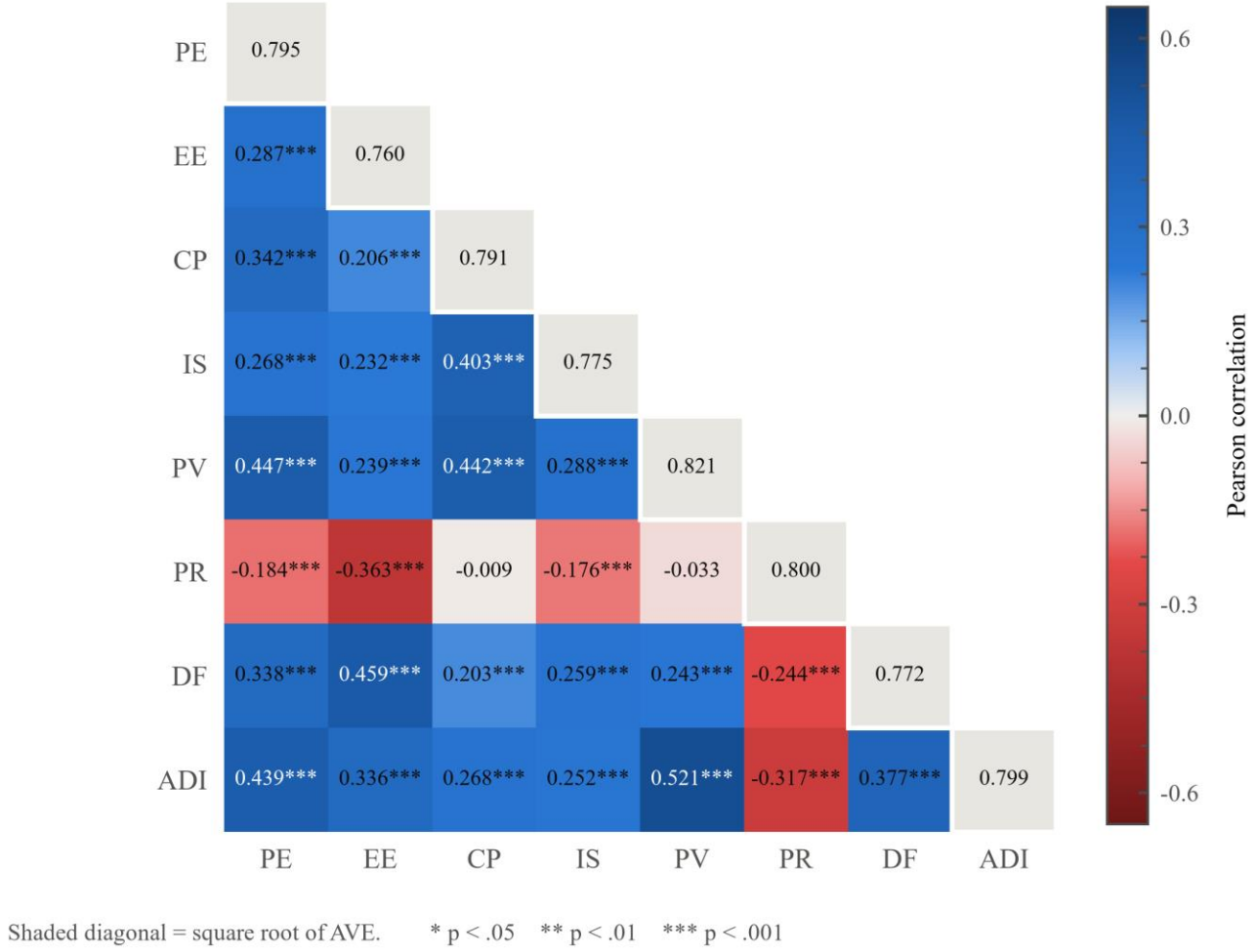


Figure 3. Correlations among constructs and discriminant validity. Source: Authors.

4.4. Common Method Bias

Three tests were run in parallel. Harman's single-factor analysis extracts eight factors with eigenvalues above 1 in the unrotated solution, the first accounting for 28.00% of the variance, below the 40% cut-off. Adding a common latent factor loaded by all 32 items to the eight-factor model returns $\chi^2 = 570.27$, $df = 396$, CFI = 0.981 and RMSEA = 0.029, with a mean squared method loading of 0.181, so method variance stands at 18.1% and falls below the 25% rule of thumb (Podsakoff et al., 2003). The largest variance inflation factor among the eight constructs, 1.452, is below the 3.3 criterion of Kock (2015), so the full collinearity test finds no inflation attributable to method variance. The three results agree that method variance does not threaten the substantive conclusions.

4.5. Structural Model and Hypothesis Tests

The structural model returns $\chi^2 = 882.77$, $df = 606$, $\chi^2/df = 1.457$, CFI = 0.970, TLI = 0.967, GFI = 0.912, AGFI = 0.902, RMSEA = 0.030 and SRMR = 0.038. R^2 is 0.475 for perceived value, 0.304 for perceived implementation risk and 0.648 for adoption intention. Path estimates appear in Table 5 and the path diagram in Figure 4.

Table 5. Structural path estimates and hypothesis tests.

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Hypothesis	Path	*b*	*S.E.*	*z*	*p*	β	Result
H1a	Performance expectancy → Perceived value	0.438	0.056	7.817	< .001	0.382	Supported
H2a	Effort expectancy → Perceived value	0.061	0.053	1.157	.247	0.051	Not supported
H3a	Competitive pressure → Perceived value	0.404	0.063	6.366	< .001	0.324	Supported
H4a	Institutional support → Perceived value	0.060	0.052	1.145	.252	0.055	Not supported
H1b	Performance expectancy → Perceived risk	−0.116	0.056	−2.068	.039	−0.109	Supported
H2b	Effort expectancy → Perceived risk	−0.436	0.060	−7.309	< .001	−0.398	Supported
H3b	Competitive pressure → Perceived risk	0.231	0.065	3.539	< .001	0.200	Supported
H4b	Institutional support → Perceived risk	−0.161	0.055	−2.939	.003	−0.162	Supported
H5	Perceived value → Adoption intention	0.490	0.051	9.657	< .001	0.495	Supported
H6	Perceived risk → Adoption intention	−0.221	0.046	−4.766	< .001	−0.206	Supported
H9	Digital foundation → Adoption intention	0.153	0.051	2.986	.003	0.147	Supported
	Performance expectancy → Adoption intention	0.182	0.055	3.306	.001	0.160	n.a.
	Effort expectancy → Adoption intention	0.053	0.061	0.864	.388	0.045	n.a.
	Competitive pressure → Adoption intention	−0.067	0.060	−1.121	.262	−0.055	n.a.
	Institutional support → Adoption intention	0.011	0.047	0.232	.816	0.010	n.a.
	Firm size → Adoption intention	0.116	0.034	3.371	.001	0.113	n.a.
	Executive age → Adoption intention	−0.125	0.035	−3.576	< .001	−0.121	n.a.
	Executive education → Adoption intention	0.057	0.034	1.671	.095	0.055	n.a.
	Industry → Adoption intention	−0.068	0.068	−0.999	.318	−0.033	n.a.
	Executive age → Perceived risk	0.137	0.040	3.423	.001	0.144	n.a.
	Firm size → Perceived value	0.072	0.038	1.876	.061	0.069	n.a.

Note: b = unstandardised estimate; β = standardised estimate. All tests are two-tailed and evaluated at the .05 level (Section 3.3). H1b (b = −0.116, β = −0.109, p = .039) carries the hypothesised negative sign and reaches that level, and is therefore recorded as supported, although it is the weakest of the four estimates on the risk side. Source: Authors.

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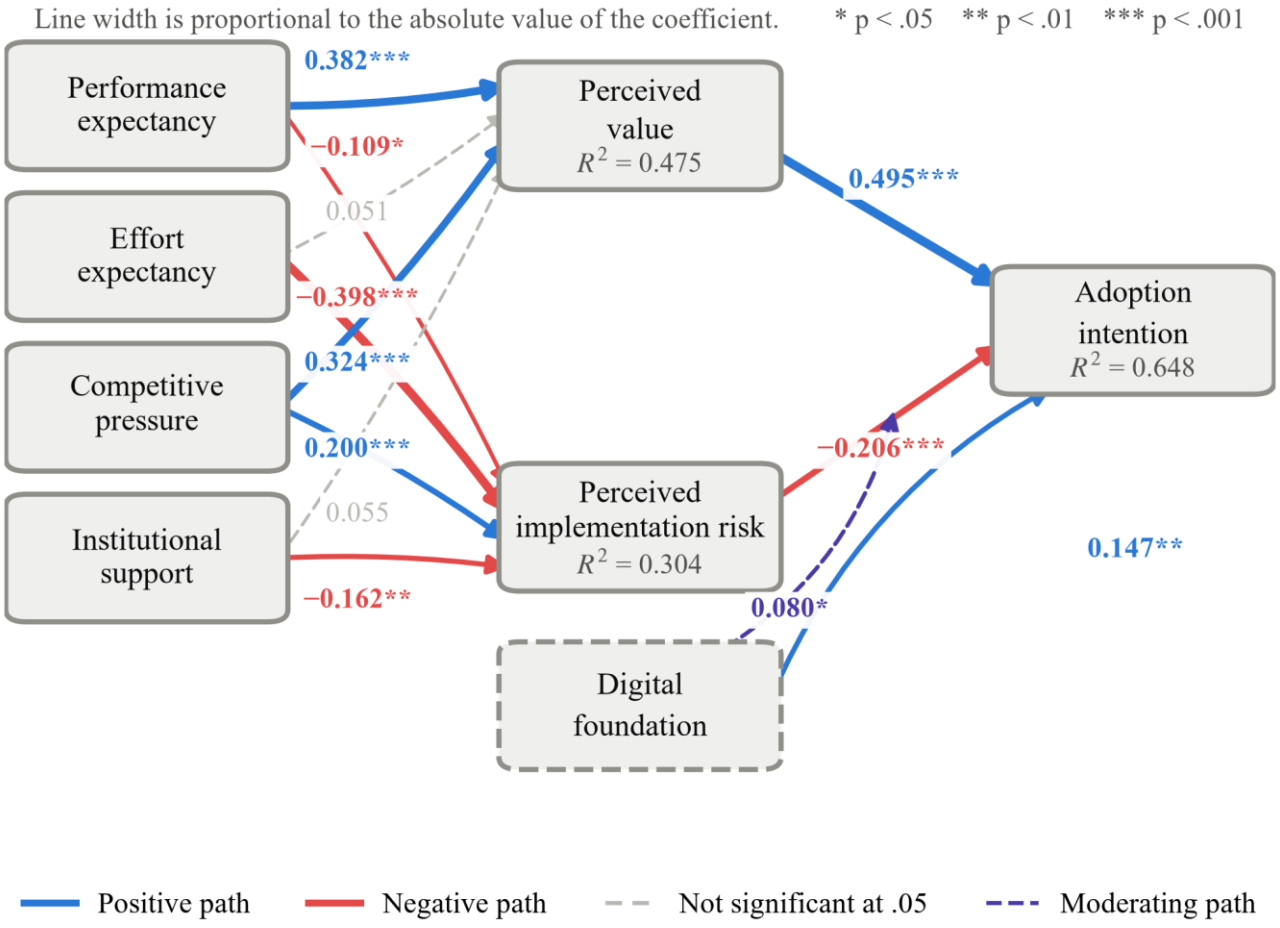


Figure 4. Standardised path estimates of the structural model. Source: Authors.

Of the four antecedents, performance expectancy and competitive pressure raise perceived value at 0.382 and 0.324, while the corresponding estimates for effort expectancy and perceived institutional support are 0.051 with $p = .247$ and 0.055 with $p = .252$, leaving H2a and H4a unsupported. On the risk side all four estimates reach the .05 level: effort expectancy lowers risk perception most strongly at −0.398, competitive pressure is the only antecedent that raises it at 0.200, and performance expectancy and institutional support come in at −0.109 and −0.162. The coefficient from perceived value to adoption intention, 0.495, is 2.40 times that from perceived implementation risk, −0.206. Among the controls, firm size and executive age enter the intention equation at the .01 level, and executive age also raises risk perception at 0.144, $p = .001$. H1b is recorded as supported under the rule stated in Section 3.3: the estimate carries the hypothesised negative sign and $p = .039$ falls below the two-tailed .05 criterion. It is at the same time the weakest of the four estimates on the risk side, $\beta = -0.109$ against −0.398 for effort expectancy, and the indirect effect it generates is 0.022, so the hypothesis is retained as a small effect and none of the conclusions of this study rests on it.

4.6. Competing Models

Four alternative specifications were compared following Anderson and Gerbing (1988), with results in Table 6. M0 is the hypothesised model, retaining the four direct paths from the antecedents to intention; M1 deletes those four; M2 deletes the mediation through the two intermediate constructs and keeps only direct effects; M3 keeps perceived value as the single pathway. M0 and M1 are nested, and $\Delta\chi^2(4) = 11.79$, $p = .019$, so the four direct paths contribute jointly at the .05 level and M0 is preferred. In M2, CFI falls to 0.958, RMSEA rises to 0.036 and SRMR to 0.048: removing the mediation stage degrades fit across the board. The SRMR of M3, 0.041, exceeds the 0.038 of M0, so a single value pathway does not absorb the structural information in the data. M0 attains the best value on all four of CFI, TLI, RMSEA and SRMR.

Table 6. Comparison of competing models.

Model	Specification	χ^2	*df*	χ^2/df	CFI	TLI	RMSEA	SRMR
M0	Dual-channel model + direct paths (hypothesised)	882.77	606	1.457	0.970	0.967	0.030	0.038

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M1	Dual-channel model, no direct paths	894.56	610	1.466	0.970	0.966	0.030	0.039
M2	Direct paths only, no mediation	963.84	572	1.685	0.958	0.953	0.036	0.048
M3	Perceived value as the single pathway	916.61	608	1.508	0.967	0.964	0.031	0.041

Source: Authors.

The two incremental fit indices are compared in Figure 5. M0 and M1 tie on CFI, M0 is marginally higher on TLI, and M2 is lowest on both. The two residual-based indices appear in Figure 6. M0 attains the smallest value on RMSEA and on SRMR, and the gap between M2 and M0 is widest on SRMR, 0.048 against 0.038.

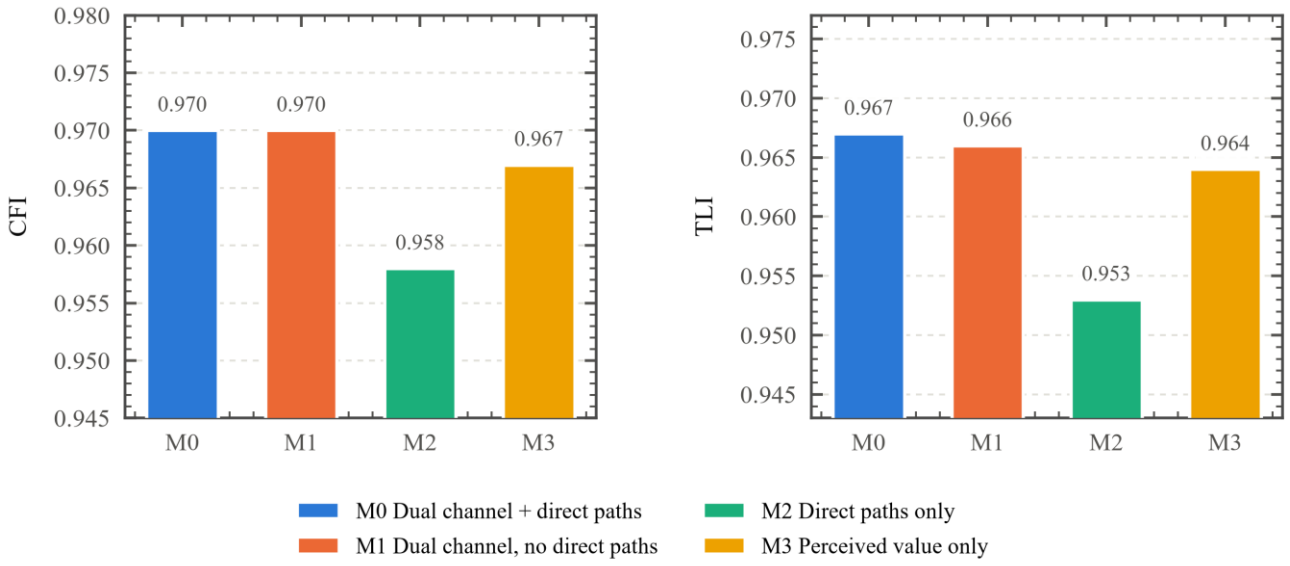


Figure 5. Incremental fit indices of the four competing models. Source: Authors.

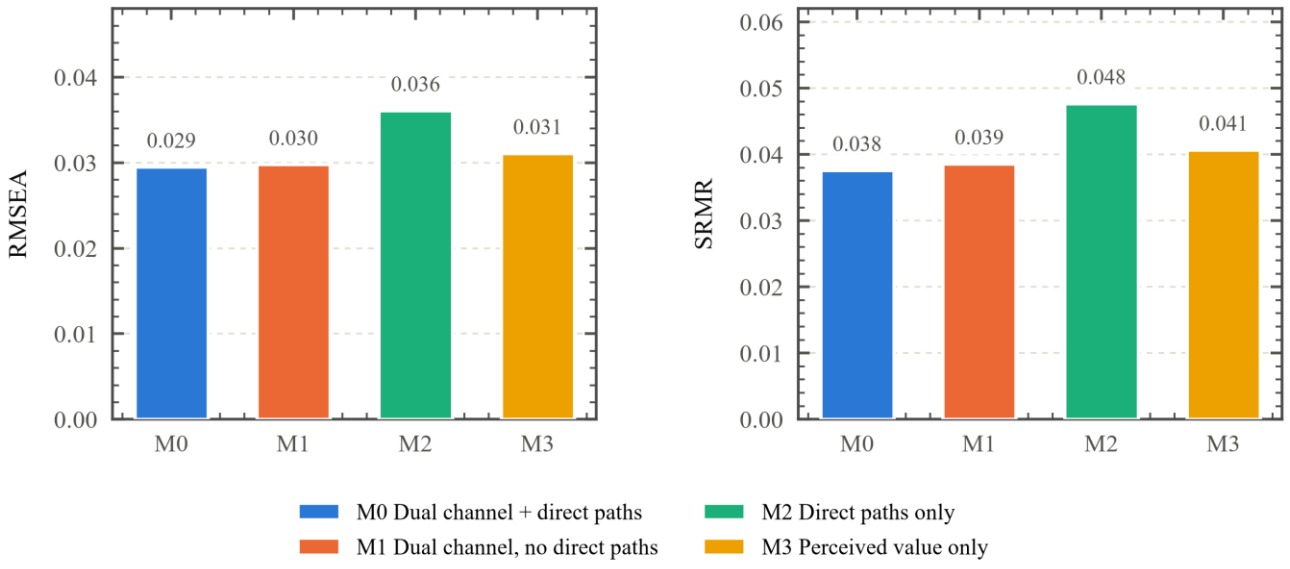


Figure 6. Residual-based fit indices of the four competing models. Source: Authors.

4.7. Bootstrap Tests of the Two Pathways

Results from 5,000 bias-corrected bootstrap resamples appear in Table 7. Six of the eight indirect effects have 95% intervals excluding zero. The indirect effect of performance expectancy is 0.189 [0.134, 0.252] through perceived value and 0.022 [0.002, 0.050] through perceived implementation risk, supporting H7a and H8a. The indirect effect of effort expectancy is 0.082 [0.045, 0.125] through perceived risk, supporting H8b, while its indirect effect through perceived value has an interval of [−0.012, 0.065] that contains zero, leaving H7b unsupported. The indirect effect of competitive pressure is 0.160 [0.104, 0.220] through perceived value and −0.041 [−0.076, −0.017] through perceived risk, supporting H7c and H8c. The indirect effect of institutional support is

0.033 [0.011, 0.067] through perceived risk, supporting H8d, while its indirect effect through perceived value has an interval of [−0.019, 0.075] that contains zero, leaving H7d unsupported.

Table 7. Bias-corrected bootstrap tests of mediation through the two pathways with 5,000 resamples.

Antecedent	Effect	Estimate	Boot *S.E.*	95% CI Lower	95% CI Upper	Result
Performance expectancy	Via perceived value	0.189	0.030	0.134	0.252	Supported
	Via perceived risk	0.022	0.012	0.002	0.050	Supported
	Total indirect	0.212	0.032	0.153	0.277	Supported
	Direct	0.160	0.052	0.052	0.259	Supported
	Total	0.371	0.051	0.267	0.467	Supported
Effort expectancy	Via perceived value	0.025	0.019	−0.012	0.065	Not supported
	Via perceived risk	0.082	0.020	0.045	0.125	Supported
	Total indirect	0.107	0.028	0.054	0.162	Supported
	Direct	0.045	0.052	−0.056	0.147	Not supported
	Total	0.152	0.051	0.055	0.254	Supported
Competitive pressure	Via perceived value	0.160	0.030	0.104	0.220	Supported
	Via perceived risk	−0.041	0.015	−0.076	−0.017	Supported
	Total indirect	0.119	0.033	0.054	0.183	Supported
	Direct	−0.055	0.047	−0.146	0.038	Not supported
	Total	0.064	0.051	−0.037	0.161	Not supported
Institutional support	Via perceived value	0.027	0.024	−0.019	0.075	Not supported
	Via perceived risk	0.033	0.014	0.011	0.067	Supported
	Total indirect	0.061	0.026	0.009	0.113	Supported
	Direct	0.010	0.046	−0.081	0.100	Not supported
	Total	0.071	0.050	−0.026	0.168	Not supported

Source: Authors.

The composition of each antecedent's effect appears in Figure 7. The structure differs sharply across the four. The total effect of performance expectancy is 0.371, of which the indirect portion accounts for 56.97% and the direct portion of 0.160 has an interval excluding zero, so the value judgement carries more than half the total effect without displacing the direct link. The total effect of effort expectancy is 0.152, of which the indirect portion accounts for 70.47% while the direct effect has an interval containing zero, so its action on intention runs entirely through the two intermediate constructs, with the risk pathway at 0.082, which is 3.23 times the value pathway at 0.025.

Competitive pressure produces the most distinctive pattern in the table. The value pathway contributes 0.160 and the risk pathway −0.041, the latter cancelling 25.71% of the former; the direct effect is −0.055 with an interval containing zero, and the total effect falls back to 0.064 with a 95% interval of [−0.037, 0.161] that includes zero. The net push of competitive pressure on adoption intention is statistically indistinguishable from zero, the result of two pathways of opposite sign, which is the classic form of a suppression effect. The total effect of institutional support, 0.071, has an interval of [−0.026, 0.168] that likewise contains zero, and its entire effective contribution of 0.061 is concentrated in the risk pathway.

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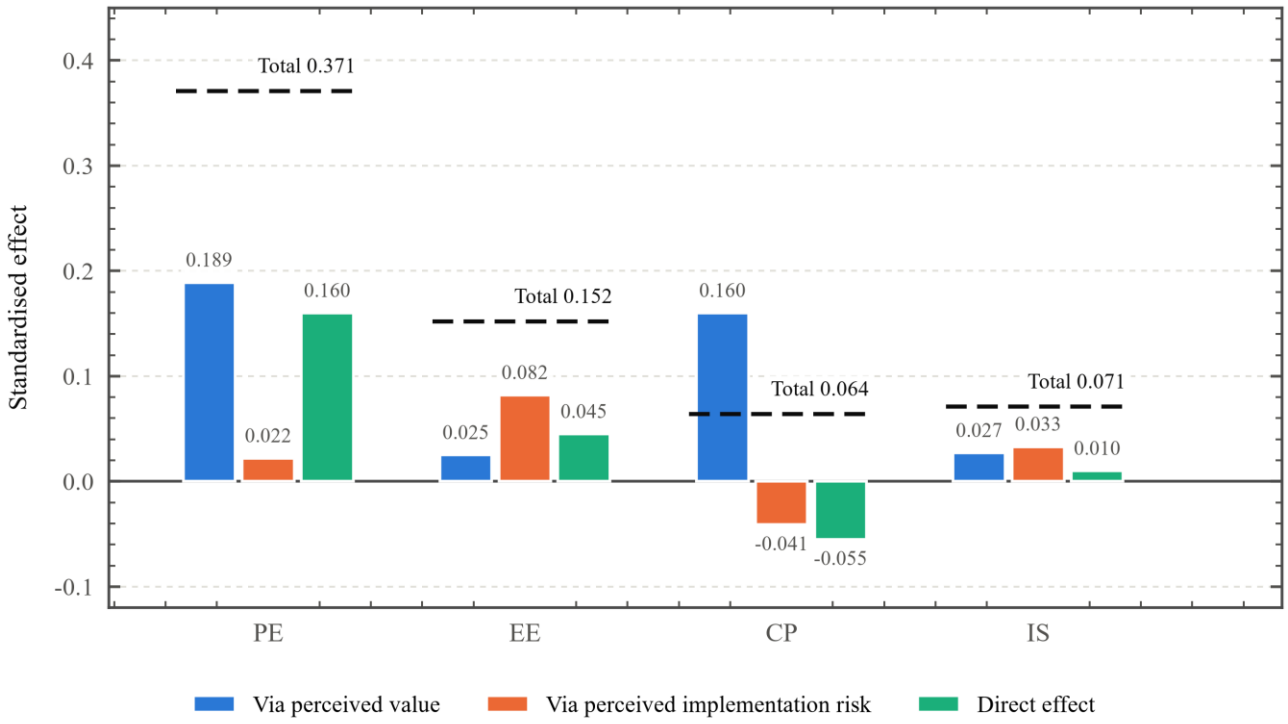


Figure 7. Decomposition of the effects of the four antecedents across the two pathways. Source: Authors.

Point estimates and intervals for the eight indirect effects and four total effects appear in Figure 8. The four intervals that cross zero fall into two places: the value pathway for effort expectancy and institutional support, and the total effects of competitive pressure and institutional support.

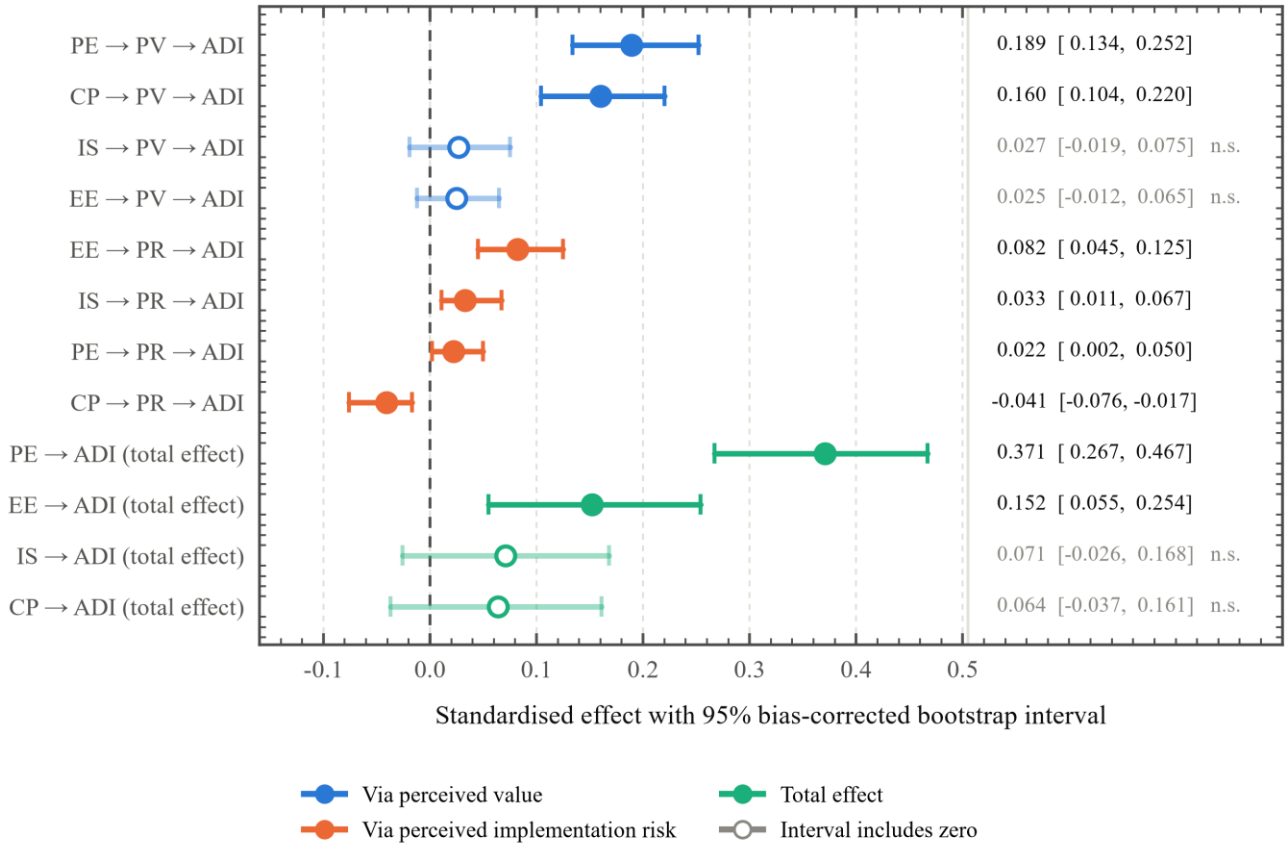


Figure 8. Bootstrap confidence intervals for indirect and total effects. Source: Authors.

4.8. The Moderating Effect of Digital Foundation

Hierarchical regression results appear in Table 8. M1 enters only the five controls, $R^2 = 0.030$. M2 adds the seven main effects and R^2 rises to 0.450, $\Delta R^2 = 0.420$, $F(7, 513) = 55.926$, $p < .001$. M3 adds the two product terms, $R^2 = 0.457$, $\Delta R^2 = 0.007$, $F(2, 511) = 3.272$, $p = .039$. The product of digital foundation and perceived implementation risk has a coefficient of 0.080, $t = 2.558$, $p = .011$, supporting H10; the product with perceived value has a coefficient of −0.002, $t = -0.062$, $p = .951$, leaving H11 unsupported. The size of that increment deserves a plain statement. $\Delta R^2 = 0.007$ means the two product terms account for seven-tenths of one percent of the variance in adoption intention, against 0.420 for the block of main effects. The interaction is reliable at the .05 level and its shape is interpretable, as the simple slopes below show, but it is a modest boundary effect rather than a large one, and the claims drawn from it in Sections 5.2 and 5.4 are held to that scale.

Table 8. Hierarchical regression for the moderating effect of digital foundation on adoption intention.

Variable	M1 β	M1 *p*	M2 β	M2 *p*	M3 β	M3 *p*
Firm size	0.113	.009	0.118	< .001	0.116	< .001
Firm age	−0.016	.711	−0.005	.872	−0.004	.894
Executive age	−0.129	.003	−0.122	< .001	−0.118	< .001
Executive education	0.004	.923	0.053	.110	0.050	.132
Industry	−0.058	.503	−0.066	.328	−0.065	.336
Performance expectancy			0.178	< .001	0.179	< .001
Effort expectancy			0.050	.210	0.048	.223
Competitive pressure			−0.013	.735	−0.006	.889
Institutional support			0.023	.540	0.022	.548
Perceived value			0.392	< .001	0.395	< .001
Perceived implementation risk			−0.199	< .001	−0.204	< .001
Digital foundation			0.148	< .001	0.147	< .001
Digital foundation × Perceived risk					0.080	.011
Digital foundation × Perceived value					−0.002	.951
R^2	0.030		0.450		0.457	
Adjusted R^2	0.020		0.437		0.442	
ΔR^2	n.a.		0.420		0.007	
ΔF	n.a.		55.926		3.272	
p of ΔF	n.a.		< .001		.039	

Source: Authors.

Simple slope tests appear in Table 9 and Figure 9. One standard deviation below the mean of digital foundation, the slope from perceived implementation risk to adoption intention is −0.284 ($t = -5.732$, $p < .001$); at the mean it is −0.204 ($t = -5.566$, $p < .001$); one standard deviation above the mean it falls to −0.125 ($t = -2.664$, $p = .008$), an attenuation of 56.18%. None of the three slopes crosses zero, so digital foundation weakens the strength of the suppression without changing its direction. The three simple slopes for perceived value are 0.397, 0.395 and 0.392, differing by less than 0.005, consistent with the conclusion on H11.

Table 9. Simple slopes and moderated mediation tests.

Test	Level	Estimate	*S.E.*/Boot *S.E.*	*t* or 95% CI	*p*
Perceived risk → Intention	Low digital foundation (−1 SD)	−0.284	0.050	$t = -5.732$	< .001
	Mean	−0.204	0.037	$t = -5.566$	< .001
	High digital foundation (+1 SD)	−0.125	0.047	$t = -2.664$	.008

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Perceived value → Intention	Low digital foundation (−1 SD)	0.397	0.052	$t = 7.570$	< .001
	High digital foundation (+1 SD)	0.392	0.054	$t = 7.285$	< .001
Index of moderated mediation	Performance expectancy → Risk → Intention	−0.008	0.005	[−0.022, −0.001]	n.a.
	Effort expectancy → Risk → Intention	−0.026	0.011	[−0.049, −0.008]	n.a.
	Competitive pressure → Risk → Intention	0.012	0.006	[0.003, 0.027]	n.a.
	Institutional support → Risk → Intention	−0.011	0.006	[−0.025, −0.003]	n.a.
Conditional indirect effect	Effort expectancy (low digital foundation)	0.092	0.020	[0.057, 0.138]	n.a.
	Effort expectancy (high digital foundation)	0.040	0.016	[0.010, 0.075]	n.a.
	Competitive pressure (low digital foundation)	−0.041	0.016	[−0.078, −0.016]	n.a.
	Competitive pressure (high digital foundation)	−0.018	0.010	[−0.042, −0.004]	n.a.

Source: Authors.

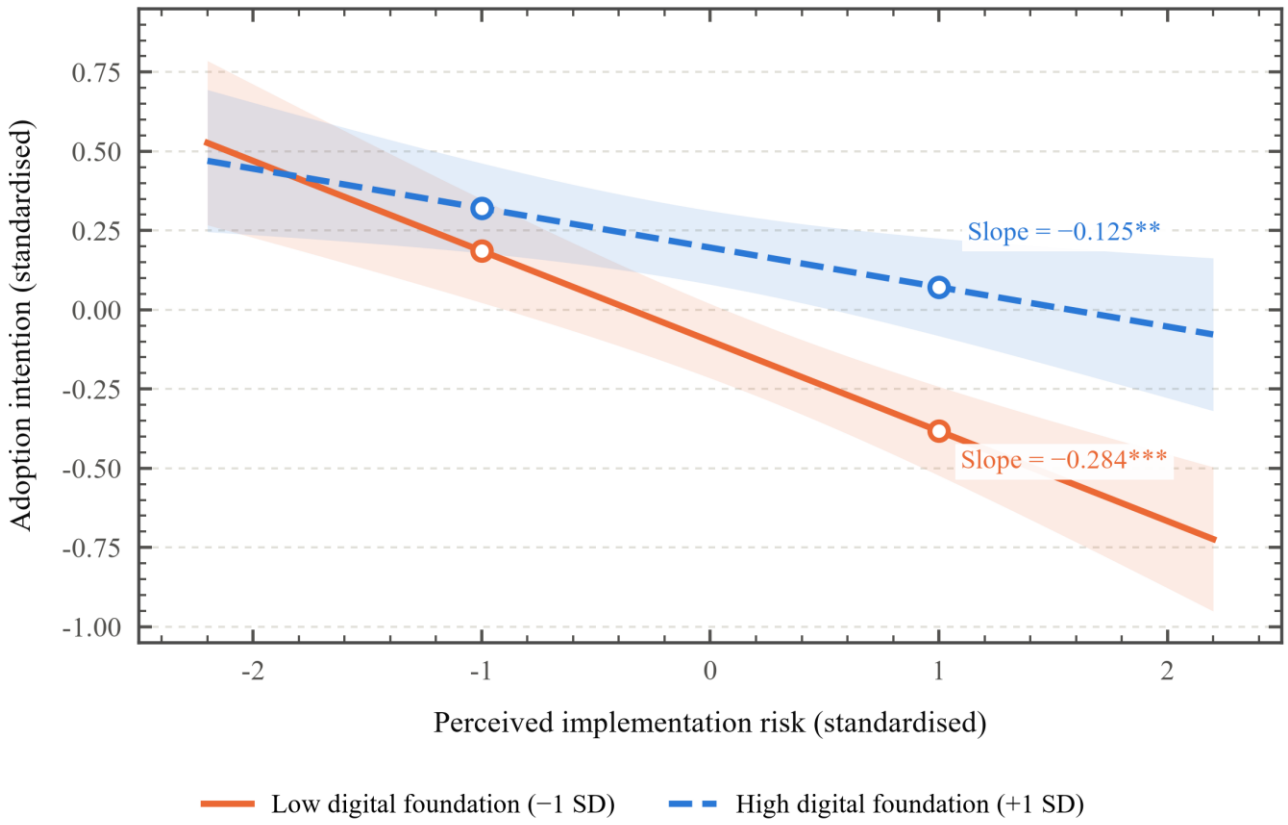


Figure 9. Digital foundation as a moderator of the link between perceived implementation risk and adoption intention. Source: Authors.

All four indirect effects running through the risk pathway are moderated by digital foundation, and every index of moderated mediation has a 95% interval excluding zero. The indirect effect of effort expectancy through the risk pathway is 0.092 in the low digital foundation group and 0.040 in the high group, a drop of 56.5%; the negative indirect effect of competitive pressure through the risk pathway narrows from −0.041 to −0.018. Digital foundation compresses the absolute magnitude of both the positive and the negative indirect effects along the risk pathway.

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4.9. Group Differences by Firm Size

The sample was split by employee count into 210 firms with 20 to 49 employees and 316 with 50 or more, and the structural model was estimated separately in each. Fit holds in both groups ($\chi^2 = 530.84$, $df = 439$, CFI = 0.976, RMSEA = 0.032; $\chi^2 = 604.75$, $df = 439$, CFI = 0.970, RMSEA = 0.035). By the test of Paternoster et al. (1998), none of the twelve path coefficients differs between the groups at the .05 level. The largest gap is the direct path from digital foundation to adoption intention, 0.239 ($p = .002$) against 0.082 ($p = .231$), $z = 1.709$, $p = .088$; the path from perceived implementation risk to adoption intention is −0.288 against −0.193, $z = -0.875$, $p = .382$. The comparison is reported as a null result: the structure holds across both size classes, and the apparently larger direct contribution of digital foundation in the smaller firms is not supported at the .05 level and is not carried into the discussion. The twelve coefficient pairs are plotted in Figure A4 in Appendix A.

5. Discussion

5.1. The Shape of the Split between the Two Pathways

The four antecedents distribute unevenly across the two pathways, and that asymmetry is the main result of the estimation. Performance expectancy is the only antecedent with a coefficient of 0.382 on the value pathway that also retains an effective direct path of 0.160, in the same direction as the findings of Chatterjee et al. (2021) in manufacturing and production firms and Pillai and Sivathanu (2020) in human resource management. The question “what will the technology do for me?” is answered consistently across differences in firm size and in the economy in which the firm operates.

The result for effort expectancy diverges from established findings on individual users. Davis (1989) and the large body of tests on end users that followed treat perceived ease of use as an antecedent of perceived usefulness. In this estimation, effort expectancy has a coefficient of 0.051 with $p = .247$ on perceived value and −0.398 with $p < .001$ on perceived implementation risk, the second of which is the largest antecedent coefficient in the model. The divergence originates in who the respondent is. End users bear the operating cost themselves, so ease of use enters their benefit calculation directly. An SME executive does not operate the system: ease of use contributes nothing directly to a profit-and-loss judgement, yet maps directly onto implementation risks of the form “the staff will not take it up after go-live” and “there will be nobody to maintain it”. A model that keeps effort expectancy as an antecedent of benefit misplaces its point of action in an executive sample.

The suppressed total effect of competitive pressure is the result among the four with the most direct bearing on practice. The value pathway contributes 0.160 and the risk pathway −0.041, opposite in sign, and the total effect of 0.064 has an interval of [−0.037, 0.161] that contains zero. Mimetic isomorphism (DiMaggio & Powell, 1983) accounts for the source of the value pathway but does not cover the compression of the firm’s own decision window by a competitor’s earlier move. The barriers of insufficient implementation capability and expected project failure that Kar and Kushwaha (2023) extract from public opinion text acquire a parameterised counterpart here: a one standard deviation increase in competitive pressure raises perceived implementation risk by 0.200 standard deviations. The one-directional positive effect of competitive pressure reported by Zhu and Kraemer (2005) and Lin (2014) on samples of medium and large firms does not reproduce in the present sample of traditional-industry SMEs. Whether that difference is attributable to firm size, to industry or to the institutional setting cannot be settled with one cross-sectional sample; what the estimates establish is that the positive total effect is absent here and that two pathways of opposite sign account for its absence. The reading proposed is that the difference lies not in whether pressure exists but in whether the firm holds the organisational buffer to absorb it.

The result for institutional support forms the counterpart to competitive pressure. Its coefficient on perceived value is 0.055 with $p = .252$ and is indistinguishable from zero, while its coefficient on perceived implementation risk is −0.162 with $p = .003$ and reaches the .01 level. The total effect of 0.071 has an interval containing zero and the total indirect effect of 0.061 has an interval excluding it. Fiscal funds, platform guidance and park matchmaking change the conditions under which failure can be borne, not the earnings outlook of the technology. Bag et al. (2021), who locate the contribution of the resource side in implementation capability rather than in adoption intention itself, point the same way.

5.2. The Two Roles of Digital Foundation

Digital foundation obtains a direct path of 0.147 with $p = .003$ and a moderating effect of 0.080 with $p = .011$, and the moderation appears only on the risk pathway. The risk slopes of −0.284 in the low digital foundation group and −0.125 in the high group differ by 56.18%, every index of moderated mediation for the four indirect effects on the risk pathway reaches the .05 level, and the three simple slopes on the value pathway differ by less than 0.005. This asymmetry says that what digital foundation buffers is the fear of not pulling the project off, not the judgement of whether it is worth the money. ERP or MES already running, staff assigned to maintenance and data that can move across departments correspond directly to the capacity to bear the three consequences named in the perceived implementation risk scale: a system that never goes live, no one available to maintain it, disruption of production.

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Whether artificial intelligence can improve delivery cycles and labour costs is judged from market and order information, which has no counterpart in the firm's internal system conditions. The moderation should be weighed at its measured size. It is consistent across the four indices of moderated mediation and legible in the simple slopes, yet the two product terms add only 0.007 to R^2, so digital foundation is best described as a condition that changes how heavily risk weighs on the decision rather than as a variable that reorganises the decision.

Alsheibani et al. (2018) treat firm-level AI readiness as a precondition for adoption and Mikalef and Gupta (2021) treat AI capability as an antecedent of performance, both remaining at the level of main effects. Xiao and Gan (2026) argue that the conversion from data possession to operations reconfiguration depends on internal data accessibility; the present result gives that argument a counterpart at the level of decision psychology, in that data accessibility matters not only for technical feasibility but because it removes more than half of the pressure risk perception exerts on the decision. The mean of digital foundation in the sample is the only one of the eight below the scale midpoint and its standard deviation is the largest, so traditional-industry SMEs are sharply divided on this condition and one and the same subsidy policy will differ in its effect through the risk pathway by a factor of about two across firms.

5.3. The Executive as the Locus of the Decision

The upper echelons argument set out in Section 2.1 can be held against the coefficients on the executive characteristics, which were entered as controls and are read here as observable proxies for the cognitive base rather than as nuisance terms. Executive age raises perceived implementation risk by 0.144 ($p = .001$) and lowers adoption intention by 0.121 ($p < .001$); executive education contributes 0.055 ($p = .095$) to intention and does not reach the .05 level. The pattern matches the mechanism Hambrick and Mason (1984) describe. Age indexes accumulated commitment to an established way of running the firm and a narrower field of vision for an unfamiliar technology, and it acts here on the risk assessment rather than on the value assessment, which is where the upper echelons account would place it. Two qualifications go with this. The estimates were not hypothesised in advance and are read after the fact, so they are offered as a reading consistent with the perspective and not as a test of it. And demographic indicators are coarse stand-ins for the cognitive base, a limitation Hambrick (2007) states directly; measuring the executive's technology experience, risk propensity and prior project history would put the argument on firmer ground. The practical reading is correspondingly narrow: where an older executive decides alone, the risk pathway is the one that carries the weight, and an outside technical opinion changes the decision conditions more than a further demonstration of benefit.

5.4. What Three Kinds of Actors Can Change

For the executives themselves. The sample mean of perceived implementation risk, 5.002, exceeds that of perceived value, 4.858, and their coefficients on intention are −0.206 and 0.495. A one standard deviation reduction in risk perception improves intention by 0.206, less than the 0.495 gained from a one standard deviation rise in value perception, yet the room to act is larger on the risk side: the coefficient of −0.398 from effort expectancy to risk means that choosing a lightweight tool with a low learning cost that fits into existing processes changes the decision conditions more than waiting for a more powerful product. The coefficient of executive age is 0.144 on risk perception with $p = .001$ and −0.121 on intention with $p < .001$, which indicates that firms where an older executive decides alone need outside technical opinion to balance that tilt.

For technology vendors. Concentrating the sales pitch on functional strength acts only on the value pathway. The indirect effect of effort expectancy through the risk pathway is 0.082 against 0.025 through the value pathway. For an SME executive, three questions therefore change the purchase decision more than performance specifications do: who will maintain the system after go-live, how long the staff will take to learn it, and how much of the existing process has to be rebuilt. Gan and Xiao (2025), analysing how generative AI reconstructs SME innovation systems, argue that algorithm-participative knowledge creation lands only where the firm already holds usable data; a vendor who extends the delivery scope from software to data preparation and maintenance hosting is in effect supplying the customer with the moderating variable.

For local authorities. The total effect of institutional support is 0.071, near zero, and its entire effective contribution of 0.061 runs through the risk pathway, which places the point of action of the current subsidy-centred policy toolkit at lowering the consequences of failure rather than at raising adoption intention. The total effect of competitive pressure is 0.064 and likewise sits near zero: publicity built on peer demonstration and benchmark cases raises the value judgement and the risk judgement together, and the two offset each other. The moderating effect of digital foundation carries a direct implication for policy sequence. Putting resources first into data digitisation, coverage by basic information systems and system maintenance manpower removes more than half of the suppression the risk pathway exerts on intention, after which the same money spent on AI application subsidies will work differently through that pathway. Gan et al. (2026), reviewing anxiety and governance transformation among low-skilled workers under artificial intelligence, note that the internal resistance provoked by technology entry requires an institutional response; writing

staff retraining and job redeployment plans into the eligibility conditions for intelligent upgrading subsidies points the same way as the present result.

A short illustration makes the arithmetic concrete. Take a metal-products firm of about eighty employees whose general manager sits near the sample mean on perceived implementation risk and one standard deviation below it on digital foundation, which describes a substantial part of this sample. Two moves are open. The first is to buy a lighter tool: a vendor proposal that reads the firm's existing order spreadsheet, needs two days of operator training and leaves the current process in place raises effort expectancy by one standard deviation, which lowers perceived implementation risk by 0.398 standard deviations and, at this firm's risk slope of −0.284, raises adoption intention by about 0.11 standard deviations, adding nothing distinguishable from zero through the value pathway. The second is to spend the year on the firm's own condition first: production records into a system, one person assigned to maintenance, order and inventory data made accessible across departments, which moves digital foundation from one standard deviation below the mean to one above. That move contributes about 0.29 standard deviations directly, at 0.147 per standard deviation, and by flattening the risk slope from −0.284 to −0.125 it removes about a further 0.16 standard deviations of drag for a firm whose risk perception stands one standard deviation above the mean. The two figures are arithmetic from the estimated coefficients rather than an observed case, and they are the clearest statement of why the sequence recommended here puts the data and systems base before the application layer. Table 10 sets out each recommendation, the estimate it rests on and the condition under which it applies.

Table 10. Recommendations, the estimates they rest on and the conditions under which they apply.

Actor	Recommended Action	Estimate the Action Rests on	Condition under Which It Applies
SME executive	Choose a tool with a low learning burden that fits existing processes before choosing the most capable one	Effort expectancy → perceived risk, β = −0.398; perceived risk → intention, β = −0.206	Acts through the risk pathway only; it adds nothing to perceived value (β = 0.051, p = .247)
SME executive	Bring an outside technical opinion into a decision taken by one senior executive	Executive age → perceived risk, β = 0.144; executive age → intention, β = −0.121	A post hoc reading of control variables (Section 5.3); applies where one executive decides alone
Local authority	Fund data digitisation, basic systems and maintenance staffing before funding AI applications	Digital foundation → intention, β = 0.147; interaction with risk, β = 0.080; risk slope −0.284 to −0.125	The increment is small (ΔR^2 = 0.007) and acts on the risk pathway; the sample mean of digital foundation is below the scale midpoint
Local authority	Do not expect publicity built on peer demonstration to raise adoption on its own	Competitive pressure: 0.160 through value, −0.041 through risk, total 0.064 [−0.037, 0.161]	A null total effect rather than an absent mechanism; holds where peer moves are quickly visible and the firm has no buffer
Local authority	Write staff retraining and job redeployment into the eligibility conditions for upgrading subsidies	Institutional support → perceived risk, β = −0.162; total effect 0.071 [−0.026, 0.168]	Support acts on the capacity to bear failure, not on the earnings outlook of the technology
Technology vendor	Sell maintenance, data preparation and training scope alongside the software	Effort expectancy: indirect effect 0.082 through risk against 0.025 through value	The vendor is in effect supplying the moderating condition; applies to customers below the sample mean on digital foundation

Source: Authors.

5.5. Theoretical Contribution

Three points can be read from the results. Each is an increment to an existing framework rather than a new theory, and each is stated at the scale the evidence supports. First, once environmental variables from the TOE framework are joined to cognitive processing at the individual level, the form of their effect changes: the one-directional positive effect of competitive pressure in organisational-level research decomposes at the executive cognitive level into two pathways of opposite sign, with the net effect falling back near zero. The gap between the two families of frameworks identified by Oliveira and Martins (2011) appears in the traditional-industry SME setting as external pressure being translated by one and the same decision maker into an opportunity and a threat at once.

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Second, perceived value and perceived implementation risk are not two ends of a single dimension. The correlation between their composite scores is −0.033 with p = .451 and the latent correlation is −0.054, and the four antecedents differ clearly in their coefficient patterns across the two pathways. M3 in the present comparison treats risk as the reverse of value and keeps a single assessment pathway, which raises SRMR from 0.038 to 0.041 and lowers CFI from 0.970 to 0.967. The independence of risk and benefit proposed by Featherman and Pavlou (2003) in the e-service setting holds equally in firm technology introduction decisions.

Third, a firm's digital condition has long been treated in adoption research as a main-effect variable or a control. The present result supplies parameterised evidence for its role as a boundary condition: the moderation appears only on the risk pathway, and the three simple slopes on the value pathway differ by less than 0.005. That asymmetry narrows the loose claim that the digital base determines adoption into the narrower claim that the digital base conditions how hard risk perception presses on the decision, within the modest incremental variance reported in Section 4.8.

5.6. Boundary Conditions and Generalisability

The estimates come from one institutional environment at one point in time, and separating what is likely to travel from what is not belongs to reporting them. Three results rest on mechanisms that are not jurisdictional. The separation of the value assessment from the risk assessment follows from the dual-factor argument of Cenfetelli (2004) and the ambivalence argument of Piderit (2000), neither of which depends on a national setting. The displacement of effort expectancy from the value side to the risk side follows from who the respondent is, an executive who does not operate the system, and should reappear in any executive sample. The buffering role of digital foundation follows from the content of the risk items, which name conditions a firm either holds or lacks. Two results are tied to the setting. Perceived institutional support is measured here as application-based subsidies, public service platforms, park matchmaking and an explicit policy category, a package characteristic of Chinese industrial policy (Peng et al., 2008); where public support reaches SMEs through tax credits, innovation vouchers or advisory networks, the content of the construct changes and the near-zero total effect reported here cannot be assumed to carry over. The near-zero net effect of competitive pressure depends on how quickly a competitor's move becomes visible, which in the dense clusters of the Yangtze and Pearl River Deltas is quicker than in dispersed industries elsewhere; Zhu et al. (2006) report cross-country variation of exactly this kind in the strength of environmental effects on assimilation. Replication in another institutional environment is the direct test, and it requires no change to the instrument beyond the wording of the institutional support items.

A second boundary concerns what the evidence can carry. The eleven hypotheses are propositions derived from the literature reviewed in Section 2; the coefficients in Section 4 are associations estimated on cross-sectional data. Where the text states that an antecedent raises or lowers an assessment, it reports the sign and size of an estimated association under the specification stated, not an observed change over time. The competing model comparison in Section 4.6 narrows the set of specifications consistent with the covariance structure; it does not establish temporal order, and the design that would is named among the limitations in Section 6.

6. Conclusions

Structural equation estimation on 526 SME executives across four regions and four traditional industries yields three conclusions. Performance expectancy and competitive pressure reach adoption intention through perceived value at 0.189 and 0.160, while the effects of effort expectancy and institutional support on perceived value are indistinguishable from zero and their contribution concentrates on lowering perceived implementation risk at −0.398 and −0.162. Competitive pressure is the only antecedent whose two pathways carry opposite signs, the risk pathway cancelling 25.71% of the value pathway, with a total effect of 0.064 whose 95% interval contains zero; the total effect of institutional support, 0.071, likewise contains zero. Digital foundation weakens the suppression that perceived implementation risk exerts on adoption intention, the slope falling from −0.284 to −0.125, an attenuation of 56.18%, with no counterpart effect on the value pathway.

Six limitations bound these conclusions. First, the data are self-reported and cross-sectional at a single point in time, so the ordering among perceived value, perceived implementation risk and adoption intention is set by theory rather than confirmed by the data, and reverse linkage cannot be excluded, since an executive who already intends to adopt may be rationalising that decision; two-wave tracking at six-month intervals or a scenario experiment would separate the directions. Second, the dependent variable is adoption intention rather than adoption behaviour, and budget approval, vendor matching and staff acceptance intervene between the two; the intention–behaviour gap identified by Ajzen (1991) may be wider in resource-constrained SMEs, and actual adoption records at twelve months would settle the question. Third, the sample covers four industries in four regions and excludes asset-heavy industries such as mining and chemicals as well as the north-west and north-east; the industry coefficient of −0.033 with p = .318 does not warrant extrapolation to all traditional industries. Fourth, the questionnaire uses "artificial intelligence" as a collective term and does not separate machine vision inspection in production, intelligent scheduling and demand forecasting in operations, and intelligent customer service at the customer end; the three differ markedly in investment scale and implementation difficulty, and the differences in organisational response across technology forms noted by Gan et al. (2026) call for re-estimation on scales

split by application type. Fifth, two constructs are measured with more error than the rest: the average variance extracted of digital foundation, 0.596, and of effort expectancy, 0.578, exceed the 0.50 threshold by a small margin and DF4 loads at 0.668, so the estimates involving them, including the moderation, are less precise than the others; a fuller digital foundation instrument covering data quality and system integration would tighten them. Sixth, the moderating effect, although consistent across the four indices of moderated mediation, adds only 0.007 to the explained variance in intention, so the boundary condition should be read as a change in the weight the risk pathway carries and not as a large reorganisation of the decision. These conclusions also come from a single institutional environment; Section 5.6 sets out which results are expected to travel and which are tied to the Chinese support package, and a replication where public support reaches SMEs through tax credits or advisory networks is the direct test.

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Institutional Review Board Statement: Ethical review and approval were waived for this study. The research consisted of an anonymous, voluntary questionnaire administered to adult company executives about technology decisions taken by their firms; it collected no personally identifiable information, no health-related data and no other sensitive personal data, and it involved no intervention, so it falls outside the categories of research requiring ethics committee approval. Respondents were informed of the purpose of the survey and of the anonymous, aggregate use of their answers before taking part, and were free to withdraw at any point. The study was conducted in accordance with the Declaration of Helsinki.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The questionnaire dataset, the SPSS and Amos output files and the syntax that support the findings of this study are available from the corresponding author on reasonable request. The data are not publicly deposited because respondents were assured that their answers would be used only in aggregate form.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

The four figures collected here support the descriptive and robustness statements in Sections 4.1, 4.2 and 4.9. They were moved out of the main text so that the argument runs from the measurement model through to the structural estimates without interruption.

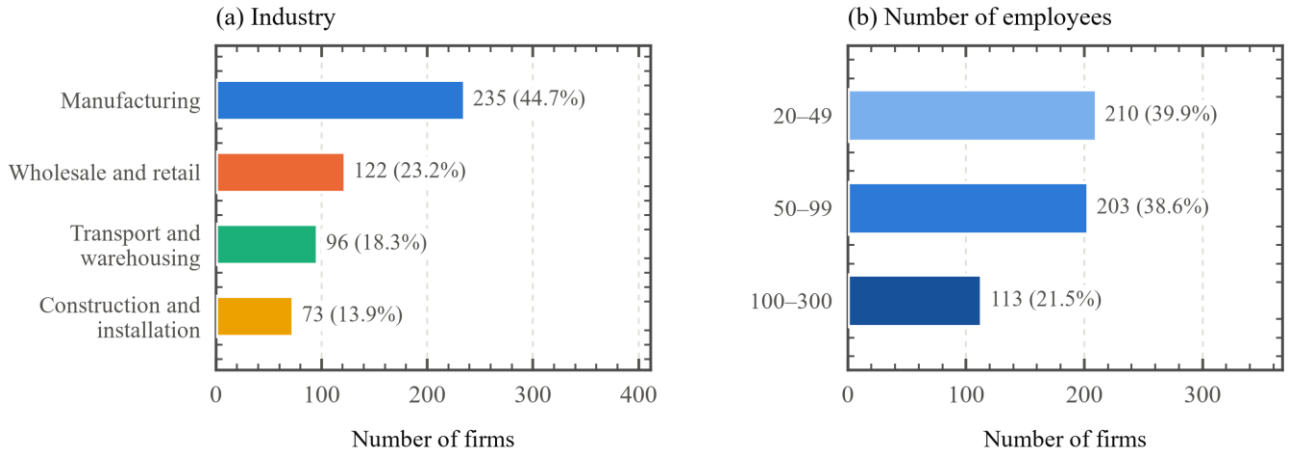


Figure A1. Industry and size distribution of the sampled firms. Source: Authors.

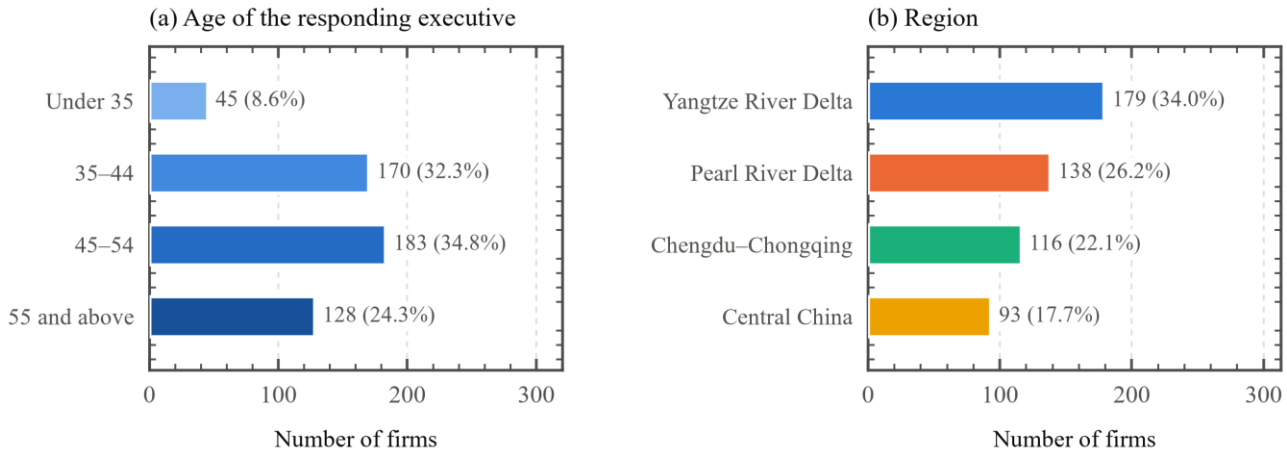


Figure A2. Age of the responding executives and regional distribution of the sample. Source: Authors.

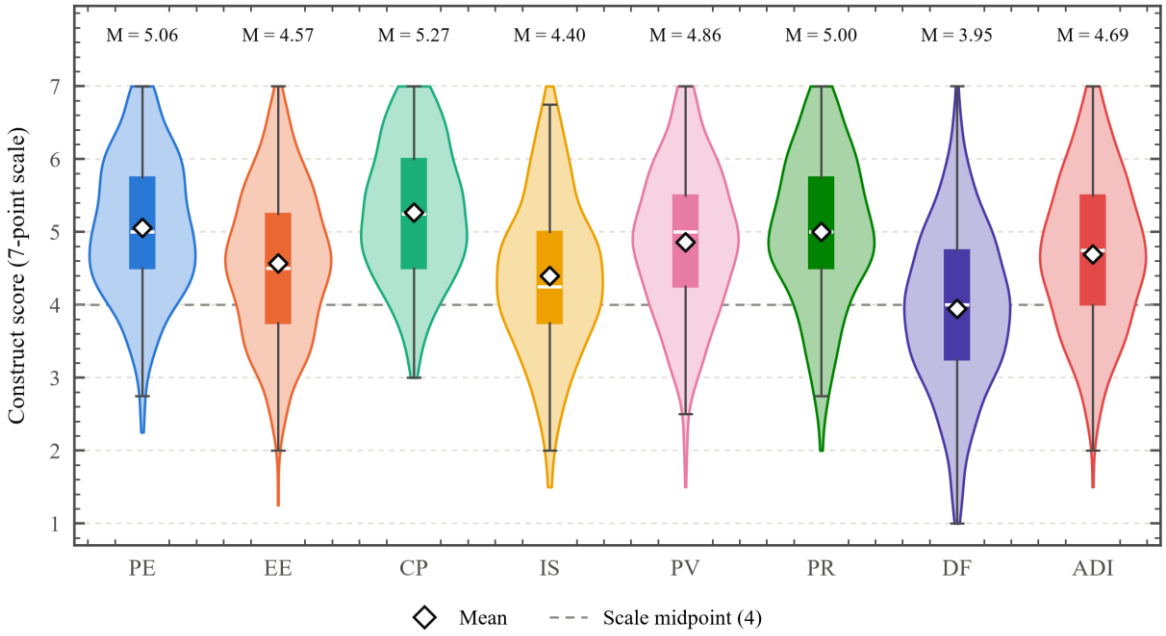


Figure A3. Score distributions of the eight constructs. Source: Authors.

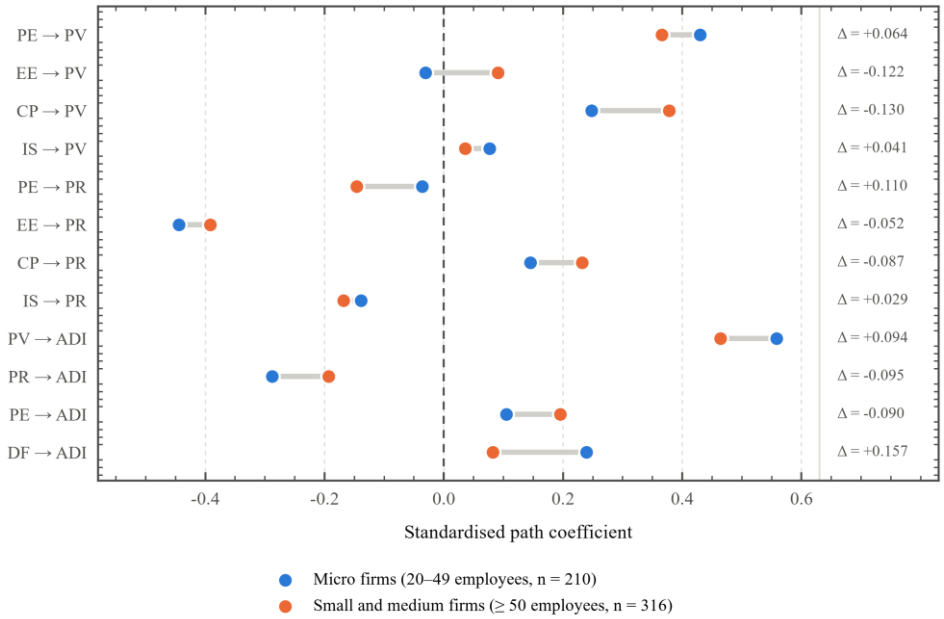


Figure A4. Comparison of path coefficients between the two firm-size groups. Source: Authors.

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