Extending the Technology Acceptance Model to Generative AI at Work: A Conceptual Framework Linking Acceptance Beliefs to the Job Performance of Generation Z Employees in Bangkok

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Abstract

The rapid diffusion of generative artificial intelligence into everyday work has made employee acceptance, rather than technical capability alone, the decisive condition under which such tools translate into productivity. This paper develops a conceptual framework that extends the Technology Acceptance Model to the use of generative artificial intelligence by Generation Z employees working in public and private organisations in Bangkok. The paper is conceptual: it synthesises the acceptance literature, the contemporary evidence on artificial intelligence in organisations, and the performance-appraisal tradition in human resource management, and it reports no empirical data. Three acceptance beliefs drawn from the model, namely perceived usefulness, perceived ease of use and attitude toward using, are defined, decomposed into observed variables, and linked to employee performance conceptualised through the dimensions of accuracy and quality, quantity of output, time, quality of delivered work and overall efficiency. Three principal propositions relate each acceptance belief positively to employee performance, and two auxiliary propositions reproduce the internal structure of the acceptance model for future extension. The paper further proposes a research design in which a five-point Likert questionnaire, validated through item-objective congruence assessment and a pilot test of reliability, would be administered to a sample of Generation Z employees in Bangkok and analysed with multiple linear regression to derive a predictive equation for employee performance. The expected contribution is a generation-specific and context-specific acceptance model, together with a validated instrument and a testable research agenda for human capital management in Thailand.

Keywords: Technology Acceptance Model, Generative artificial intelligence, Generation Z employees, Employee performance, Conceptual framework

1. Introduction

The diffusion of artificial intelligence into the everyday routines of the workplace has become one of the defining managerial questions of the present decade. The arrival of generative systems such as conversational assistants, drafting aids and analytical copilots moved artificial intelligence out of specialised data centres and placed it directly in the hands of ordinary employees, who now use it to summarise documents, draft correspondence, interrogate data and support decisions. Bankins et al. (2024), in a multilevel review of artificial intelligence in organisations, observe that this shift produces consequences at the individual, team and organisational levels simultaneously, creating both opportunities for efficiency and behavioural challenges for the people expected to work alongside the technology. The managerial question, therefore, is no longer whether organisations will adopt such systems, but whether their employees will accept them in ways that actually improve work outcomes.

Thailand offers a particularly instructive setting for that question. Survey evidence assembled in the source literature indicates that Thai employees are unusually receptive to artificial intelligence at work, that sectors making intensive use of the technology report markedly faster labour-productivity growth than those that do not, and that possession of artificial intelligence skills has become a hiring criterion in its own right. At the same time, national data show that the most intensive users of these tools are the youngest cohort of the labour force. Table 1 summarises the contextual indicators cited in the proposal on which this paper is based, together with their sources, in order to locate the conceptual argument within a specific national environment rather than a generic one.

Within that environment, one demographic group deserves separate attention. Pew Research Center (2019) and McKinsey & Company (2023) define Generation Z as those born between the late nineteen-nineties and the early twenty-tens, the first cohort to have grown up with the internet, smartphones and social platforms embedded in daily life from early childhood. This cohort is expected to constitute close to a third of the global workforce, and evidence reported by International Workplace Group (2025) indicates that its members adopt generative tools at work considerably more often than older colleagues, frequently acting as informal coaches for them. HP Thailand (2024) similarly reports high device access, broad application use and rapid adaptation to new digital tools among young Thai employees. Bangkok, which concentrates the country's government agencies, large private firms, service businesses and financial institutions, is where this cohort is most densely employed.

The theoretical lens through which employee acceptance has most often been examined is the Technology Acceptance Model. Davis (1989) built the model on the foundations of the theory of reasoned action of Fishbein and Ajzen (1975), proposing that the use of a technology is explained principally by two beliefs, perceived usefulness and perceived ease of use, which shape the user's attitude toward using the system and, through it, intention and actual use. Venkatesh and Davis (2000) extended the model by specifying the social and cognitive determinants of usefulness, and Venkatesh et al. (2003) subsequently absorbed the two beliefs into the broader constructs of performance expectancy and effort expectancy. Applications to artificial intelligence have confirmed the model's continued explanatory value; Choung et al. (2024) report that ease of use influences attitude directly and usefulness indirectly, while Sukhumvit et al. (2025) demonstrate the relevance of acceptance constructs to actual usage behaviour in a Thai occupational setting.

Two gaps nevertheless remain. First, most empirical work on artificial intelligence acceptance samples mixed generations, so that the resulting estimates describe the average employee rather than the cohort whose working life will be most thoroughly shaped by the technology. Because Generation Z combines high technological familiarity with distinctive expectations of the working environment, aggregating it with older cohorts risks obscuring precisely the differences that human resource policy needs to address. Second, the acceptance literature has concentrated on intention and use as outcomes, while the link from acceptance beliefs to job performance itself has been examined less often and, in the Thai context, hardly at all. Park et al. (2024) further caution that employee attitudes toward artificial intelligence are multidimensional, encompassing anxiety, job insecurity and a diminished sense of ownership alongside perceived benefit, so that a positive attitude cannot be assumed from the mere availability of a capable tool.

This paper responds to those gaps conceptually rather than empirically. Its objectives are threefold: to synthesise the definitions, theoretical foundations and observable dimensions of perceived usefulness, perceived ease of use, attitude toward using and employee performance as they apply to generative artificial intelligence at work; to develop a conceptual framework and a set of research propositions linking the three acceptance beliefs to the performance of Generation Z employees in Bangkok; and to propose a research design, including instrument development, validation and analysis, through which those propositions could subsequently be tested. The intended contribution is threefold in turn: theoretically, an extension of the acceptance model in which performance rather than intention is the criterion variable; methodologically, a generation-specific and context-specific instrument; and practically, the basis for a predictive equation that human resource managers could use when designing adoption and training policy.

Table 1: Contextual indicators of artificial intelligence adoption in the Thai workplace cited in the source literature

Indicator	Reported figure	Source
Thai employees viewing artificial intelligence as a thought partner	56 per cent	Microsoft Corporation (2025)
Thai employees viewing artificial intelligence as a tool to be commanded	43 per cent	Microsoft Corporation (2025)
Labour-productivity growth in artificial-intelligence-intensive Thai sectors	4.8 times that of less intensive sectors	PwC Thailand (2024)
Thai leaders unwilling to hire candidates lacking artificial intelligence skills	74 per cent	PwC Thailand (2024)
Generation Z employees using generative tools at work	45 per cent, against 34 per cent of Generation X	International Workplace Group (2025)
Most intensive user group of artificial	Users aged 16–24 years	National Thailand (2025)

Indicator	Reported figure	Source
intelligence in Thailand		
Projected share of Generation Z in the global workforce	Close to 30 per cent	McKinsey & Company (2023)

Source: Compiled by the authors from the reports cited in the source proposal.

2. Theoretical Background

2.1 The Technology Acceptance Model as Theoretical Anchor

The Technology Acceptance Model originated in the practical puzzle of why technically superior systems were sometimes rejected by their intended users. Davis (1989) argued that the determinants of use lie not in the engineering characteristics of a system but in the beliefs users hold about it, and adapted the reasoned-action framework of Fishbein and Ajzen (1975), in which behaviour follows from intention, intention from attitude and subjective norm, and attitude from beliefs about outcomes. Two beliefs were held to dominate in the technology domain: the belief that the system improves job performance, and the belief that using it requires little effort. Davis et al. (1989) formalised the resulting causal chain and demonstrated its superiority over the general reasoned-action model in predicting information-system use.

Subsequent theoretical work broadened rather than displaced the model. Ajzen (1991) added perceived behavioural control to the reasoned-action tradition, and Mathieson (1991) compared the two frameworks directly, concluding that the acceptance model predicted intention comparably well while being more parsimonious and more readily transferable across technologies. Venkatesh and Davis (2000) specified the social and cognitive antecedents of usefulness, including subjective norm, image, job relevance, output quality and result demonstrability, and Venkatesh et al. (2003) integrated these strands into a unified account in which performance expectancy is the strongest predictor of intention. Two adjacent theories underpin the ease-of-use construct in particular: the social cognitive account of Bandura (1986), in which self-efficacy beliefs govern the effort a person will invest in a task, and the cognitive load theory of Sweller (1988), which explains why systems that economise on mental effort are adopted more readily.

2.2 Perceived Usefulness

Davis (1989) defined perceived usefulness as the degree to which a person believes that using a particular system would enhance his or her job performance. Two features of that definition matter for the present framework. Usefulness is an evaluation made by the user rather than a property of the system, and it is directed at the outcomes of the user's own work rather than at the general pleasantness of the interaction. Davis et al. (1989) accordingly treat it as an outcome belief that shapes attitude and, through it, intention. Venkatesh and Davis (2000) enriched the construct by showing that such beliefs are formed under social influence and cognitive-instrumental processes, and Venkatesh et al. (2003) generalised it as performance expectancy.

In the artificial intelligence context the construct has been elaborated further. Bankins et al. (2024) describe employee assessments of usefulness as encompassing productivity gains, faster decision-making, relief from repetitive work and support for continuous learning. Choung et al. (2024) position usefulness as the principal driver of attitude and continued-use intention among users of artificial intelligence, and Kelly et al. (2023) show in a systematic review that perceived benefit operates jointly with trust and system transparency. Park et al. (2024) add that personal utility is only one facet of a broader attitudinal structure that also contains anxiety and insecurity, while Wei et al. (2025) identify perceived usefulness as the leading driver of positive attitude and use intensity specifically among Generation Z employees. Synthesising these accounts, the present framework treats perceived usefulness as comprising five observed variables: faster task completion, improved work quality, greater manageable workload, better resolution of complex problems, and the overall value of the technology to the job.

2.3 Perceived Ease of Use

Perceived ease of use was defined by Davis (1989) as the degree to which a person believes that using a particular system would be free of physical and mental effort. Its theoretical role is that of a cost term: however capable a technology may be, a system that demands substantial learning effort is less likely to be integrated into routine work. Mathieson (1991) framed the construct as an assessment of how easily the system can be learned and made to do what the user wants; Venkatesh et al. (2003) reformulated it as effort expectancy, comprising clarity, ease and learnability. Bandura (1986) supplies the psychological mechanism, since users with higher self-efficacy interpret the same interface as requiring less effort, and Sweller (1988) supplies the design implication, since systems that reduce extraneous cognitive load are accepted more readily.

For generative artificial intelligence, ease of use has acquired new content. Choung et al. (2024) describe it in terms of learnability, interface clarity, flexibility and controllability, while Kelly et al. (2023) emphasise the roles of transparency and explainability in shaping whether a system feels tractable. Wei et al. (2025) report that Generation Z employees, whose fluency with digital tools is high, assess conversational interfaces as unusually easy to operate. The framework therefore represents perceived ease of use through five observed variables: overall ease of use, ease of learning, clarity and comprehensibility of the interface, the level of mental effort required, and the felt ability to control and direct the system.

2.4 Attitude Toward Using

Attitude occupies the mediating position in the acceptance chain. Fishbein and Ajzen (1975) define it as an overall evaluation of an object or behaviour formed from outcome beliefs and the evaluation of those outcomes, and Ajzen (1991) retains it as a determinant of intention within the theory of planned behaviour. Davis (1989) transposed the construct into the technology domain as the user's positive or negative feeling about using a particular system, and Davis et al. (1989) elaborated it as liking, satisfaction, confidence in results and willingness to continue using the system. Mathieson (1991) confirmed its filtering role between belief and behaviour.

Contemporary work on artificial intelligence treats attitude as decidedly multidimensional. Park et al. (2024), in developing a scale of attitudes toward artificial intelligence at work, characterise it as a cognitive-affective evaluation of the integration of the technology into working life, and their companion study frames employee attitudes as combining perceived usefulness with anxiety and job insecurity. Kelly et al. (2023) show that trust, transparency and perceived risk condition these evaluations, and Wei et al. (2025) find that Generation Z employees are open and broadly positive while remaining wary of over-dependence and of the erosion of their own judgement. The framework consequently operationalises attitude toward using through satisfaction with use, confidence in and trust in the outputs, willingness to continue using the technology, appraisal of its worth relative to the time invested, and confidence in its capability.

2.5 Employee Performance

Employee performance is the criterion variable of the framework and is drawn from the human resource management tradition rather than from the acceptance literature. Bernardin and Russell (1998) define it as the record of outcomes produced over a specified period and assessed against the goals or standards set for the job, and propose six appraisal dimensions covering quality, quantity, timeliness, cost-effectiveness, need for supervision and interpersonal impact. Campbell et al. (1993) offer a behavioural theory of performance in which multiple components jointly serve organisational goals, and Mathis and Jackson (2010) present a comparable practitioner framework built on quantity, quality, timeliness, attendance and cooperation. Table 2 sets out the definitions on which each construct in this paper rests, together with the working definition adopted here.

Applying these frameworks to work mediated by generative artificial intelligence requires some adjustment. Bankins et al. (2024) find that employees who perceive artificial intelligence as useful display better outcomes in productivity, decision quality and speed, while the survey reported by Microsoft Corporation (2025) associates viewing the technology as a thought partner with higher productivity and job satisfaction. PLOS One (2024) reports a positive association between generative artificial intelligence use and innovative job performance, and PwC Thailand (2024) documents the macro-level productivity differential between more and less intensive adopters. Following the proposal, the present framework retains five observed variables for employee performance: accuracy and thoroughness of work, quantity of output, time required per task, quality of delivered work, and overall working efficiency. Table 3 maps all four constructs to their observed variables and to the sources from which those variables were synthesised.

Table 2: Definitions of the four constructs across key authors and the working definitions adopted

Construct	Representative definitions in the literature	Working definition adopted in this paper
Perceived usefulness	Belief that using a system enhances job performance (Davis, 1989); outcome belief leading to better performance (Davis et al., 1989); performance expectancy (Venkatesh et al., 2003)	The Generation Z employee's belief that using artificial intelligence at work raises his or her own work outcomes
Perceived ease of use	Belief that using a system is free of effort (Davis, 1989); ease of learning and of making the system comply (Mathieson, 1991); effort expectancy (Venkatesh et al., 2003)	The employee's belief that using artificial intelligence requires no excessive physical or mental effort
Attitude toward using	Overall evaluation formed from outcome beliefs (Fishbein & Ajzen, 1975); positive or negative feeling about using a system (Davis, 1989); multidimensional workplace evaluation (Park et al., 2024)	The employee's positive or negative feelings, opinions and evaluation of adopting artificial intelligence in work
Employee performance	Outcomes produced in a period against job standards (Bernardin & Russell, 1998); multi-component behavioural theory (Campbell et al., 1993); output, quality and timeliness (Mathis & Jackson, 2010)	Work outcomes achieved by the employee after adopting artificial intelligence, judged against job goals or standards

Source: Synthesised by the authors from the cited literature.

Table 3: Constructs, proposed observed variables and representative sources

Construct	Proposed observed variables	Representative sources
Perceived usefulness	Faster completion; improved quality; greater workload managed; solving complex problems; overall value to the job	Davis (1989); Venkatesh and Davis (2000); Bankins et al. (2024); Choung et al. (2024); Wei et al. (2025)
Perceived ease of use	Overall ease; ease of learning; interface clarity; mental effort required; sense of control	Davis (1989); Mathieson (1991); Bandura (1986); Sweller (1988); Kelly et al. (2023)
Attitude toward using	Satisfaction; confidence in outputs; willingness to continue; appraisal of worth; confidence in capability	Fishbein and Ajzen (1975); Ajzen (1991); Davis et al. (1989); Choung et al. (2024); Park et al. (2024)
Employee performance	Accuracy and thoroughness; quantity of output; time per task; quality of delivered work; overall efficiency	Bernardin and Russell (1998); Campbell et al. (1993); Mathis and Jackson (2010); Microsoft Corporation (2025); Wei et al. (2025)

Source: Synthesised by the authors from the cited literature.

3. Conceptual Framework and Propositions

The framework proposed here retains the belief structure of the acceptance model but replaces intention with realised job performance as the criterion variable. It contains three exogenous constructs, namely perceived usefulness, perceived ease of use and attitude toward using, each measured through five observed variables, and one endogenous construct, employee performance, measured through five observed variables drawn from the appraisal tradition. The three acceptance beliefs are modelled as parallel predictors of performance within a single-level regression structure, consistent with the analytical design of the underlying proposal, and each is expected to exert a positive influence. Demographic characteristics of the respondent, comprising sex, age band within the cohort, level of education and type of employing organisation, are treated as descriptive covariates rather than as substantive predictors. The framework is deliberately parsimonious, since its purpose is to establish whether acceptance beliefs carry predictive weight for performance in a specific cohort and locality before more elaborate mediated structures are entertained.

3.1 Perceived Usefulness and Employee Performance

The proposition that beliefs about usefulness translate into better work outcomes is the oldest claim in the acceptance literature and remains the best supported. Davis (1989) demonstrated a strong association between perceived usefulness and system use, and Venkatesh and Davis (2000) traced the belief through four longitudinal field studies in which it accounted for a substantial share of the variance in intention across stages of experience. In the artificial intelligence context, Bankins et al. (2024) synthesise evidence that employees who assess these systems as useful perform better in productivity, decision quality and speed, and Choung et al. (2024) report direct and indirect effects on continued use. Among Generation Z employees specifically, Wei et al. (2025) identify perceived usefulness as the principal driver of use intensity, while PLOS One (2024) links generative artificial intelligence use to innovative job performance and PwC Thailand (2024) documents the corresponding productivity differential at sector level. Proposition 1 (P1): Perceived usefulness of artificial intelligence exerts a positive influence on the job performance of Generation Z employees in Bangkok.

3.2 Perceived Ease of Use and Employee Performance

Ease of use contributes to performance by lowering the effort price of adoption, thereby raising the frequency and range of application until the technology becomes embedded in routine work. Davis (1989) reported a consistent association between ease of use and actual use and suggested that ease of use may be causally antecedent to usefulness. Venkatesh et al. (2003) show that effort expectancy predicts intention and behaviour, and Choung et al. (2024) find that ease of use influences attitude directly and intention indirectly through usefulness in artificial intelligence settings. Kelly et al. (2023) confirm the construct's consistency across a large body of acceptance research, and in the Thai context Sukhumvit et al. (2025) demonstrate that effort-related expectations shape actual usage behaviour, which in turn conditions subsequent work outcomes. Proposition 2 (P2): Perceived ease of use of artificial intelligence exerts a positive influence on the job performance of Generation Z employees in Bangkok.

3.3 Attitude Toward Using and Employee Performance

Attitude converts beliefs into sustained behaviour and is therefore expected to carry independent predictive weight for performance. Davis (1989) placed attitude between beliefs and intention, and Mathieson (1991) confirmed its filtering role. Park et al. (2024) find that positive employee attitudes toward artificial intelligence raise the frequency and quality of its use at work, and their scale-development study establishes attitude as a determinant of subsequent work outcomes. Wei et al. (2025) show that among Generation Z employees a positive attitude is the mechanism that converts perceived usefulness into actual application, and Bankins et al. (2024) associate favourable attitudes with better productivity, decision quality and skill acquisition. The survey evidence reported by Microsoft Corporation (2025) points in the same direction, as does the cohort evidence of International Workplace Group (2025). Proposition 3 (P3): Attitude toward using artificial intelligence exerts a positive influence on the job performance of Generation Z employees in Bangkok.

3.4 Auxiliary Propositions within the Acceptance Chain

Beyond the three principal propositions, the literature reviewed in the source proposal also documents the internal links of the acceptance model itself, and these are stated here as auxiliary propositions that the framework accommodates but that lie outside the planned regression model. Davis et al. (1989) and Venkatesh and Davis (2000) report that ease of use operates as an antecedent of usefulness, a relationship replicated for artificial intelligence by Choung et al. (2024). Proposition 4 (P4): Perceived ease of use exerts a positive influence on the perceived usefulness of artificial intelligence. Similarly, Davis (1989), Mathieson (1991) and Kelly et al. (2023) converge on the finding that both beliefs shape attitude. Proposition 5 (P5): Perceived usefulness and perceived ease of use each exert a positive influence on attitude toward using artificial intelligence. Table 4 presents the five propositions with their relationships, supporting literature and expected direction.

Table 4: Propositions, relationships, supporting literature and expected direction

Proposition	Relationship	Supporting literature	Expected direction
P1	Perceived usefulness to employee performance	Davis (1989); Venkatesh and Davis (2000); Bankins et al. (2024); Wei et al. (2025); PLOS One (2024); PwC Thailand (2024)	Positive
P2	Perceived ease of use to employee performance	Davis (1989); Venkatesh et al. (2003); Choung et al. (2024); Kelly et al. (2023); Sukhumvit et al. (2025)	Positive
P3	Attitude toward using to employee performance	Davis (1989); Mathieson (1991); Park et al. (2024); Wei et al. (2025); Microsoft Corporation (2025)	Positive

Proposition	Relationship	Supporting literature	Expected direction
P4	Perceived ease of use to perceived usefulness	Davis et al. (1989); Venkatesh and Davis (2000); Choung et al. (2024)	Positive (auxiliary)
P5	Perceived usefulness and ease of use to attitude toward using	Davis (1989); Mathieson (1991); Kelly et al. (2023); Choung et al. (2024)	Positive (auxiliary)

Source: Synthesised by the authors from the cited literature.

4. Proposed Research Design

4.1 Population, Sample and Sampling

The study that would follow from this framework is proposed as survey research. Its population comprises Generation Z employees, defined after Pew Research Center (2019) and McKinsey & Company (2023) as those born between the late nineteen-nineties and the early twenty-tens, who work in public or private organisations located in Bangkok and who have used artificial intelligence to support their work for at least three months. Because no central register enumerates employees meeting these criteria, the population is treated as of unknown size. Two sample-size criteria are proposed in combination. Tabachnick and Fidell (2013) recommend a minimum of fifty cases plus eight per predictor for multiple linear regression, which with three predictors yields a floor of seventy-four respondents. To improve the precision of the estimates, the larger figure obtained from the standard formula for an unknown population at the ninety-five per cent confidence level, as set out by Wanichbancha (2012), is proposed instead, giving a target of three hundred and eighty-five respondents, with an additional reserve of ten per cent to absorb incomplete or ineligible returns. Convenience sampling through online channels that reach young employees in Bangkok is proposed, with screening questions confirming birth cohort, workplace location and length of experience with the technology.

4.2 Instrument Development and Validation

The proposed instrument is a closed-form electronic questionnaire in three parts. The first part records the demographic characteristics used as descriptive covariates. The second contains twenty statements, five for each construct, measured on a five-point Likert scale treated as interval data, with the interpretive bands obtained by dividing the range by the number of classes as described by Wanichbancha (2012). The third part is a single open-ended item inviting further comment, the material from which would inform discussion rather than hypothesis testing. Items for each construct are adapted from the sources identified in the literature synthesis; Table 5 presents sample items in English translation together with their conceptual origins.

Validation is proposed in two stages. Content validity would be established by submitting the draft instrument to three qualified experts in human resource management, information systems and artificial intelligence, organisational behaviour, social science research methodology, and measurement and evaluation, who would rate the congruence of each item with the research objectives. The item-objective congruence index would be computed as the mean of the expert ratings, and items falling below the conventional threshold of 0.50 would be reworded on the experts' advice or removed. The revised instrument would then be piloted with thirty respondents drawn from a group similar to but not part of the sample, and internal consistency would be assessed using the alpha coefficient of Cronbach (1951), with the criterion of 0.70 proposed by Hair et al. (2010) applied to each construct scale before the instrument is released for the main survey.

Table 5: Proposed measurement items for each construct, in English translation

Construct	Sample items (translated and adapted)	Response format	Adapted from
Perceived usefulness	Using artificial intelligence helps me complete my work more quickly; using it improves the quality of my work	Five-point Likert scale	Davis (1989); Venkatesh and Davis (2000); Bankins et al. (2024)
Perceived ease of use	Using artificial intelligence is easy for me; I can learn how to use these tools quickly	Five-point Likert scale	Davis (1989); Venkatesh et al. (2003); Choung et al. (2024)
Attitude toward	I am satisfied with using artificial	Five-point Likert	Davis et al. (1989); Kelly et al. (2023);

Construct	Sample items (translated and adapted)	Response format	Adapted from
using	intelligence in my work; I trust that it produces reliable and accurate results	scale	Park et al. (2024)
Employee performance	Since using artificial intelligence I work more accurately and thoroughly; it reduces the time each task requires	Five-point Likert scale	Bernardin and Russell (1998); Mathis and Jackson (2010); Microsoft Corporation (2025)

Source: Adapted and translated by the authors from the item tables of the source proposal.

4.3 Planned Analysis

The proposed analysis proceeds in two stages. Descriptive statistics, comprising frequencies and percentages for the demographic items and means and standard deviations for the scaled items, would characterise the sample and the level of each construct. Inferential analysis would then test the three principal propositions using multiple linear regression by the enter method at the .05 level of statistical significance, examining standardised regression coefficients, significance levels and the coefficient of determination in order to decide whether each proposition is supported. Before estimation, the assumptions of the technique would be examined, covering normality of residuals, homoscedasticity, independence of residuals assessed through the Durbin–Watson statistic, and multicollinearity among the predictors assessed through tolerance and variance inflation factors against the thresholds recommended by Hair et al. (2010). The estimated model would then be expressed as a predictive equation in which employee performance is a linear function of the three acceptance beliefs, providing the practical decision-support tool sought by the underlying proposal. Table 6 summarises the proposed design and its quality criteria.

4.4 Ethical Considerations

Because the proposed study collects self-reported data from employees about their own performance and their attitudes toward a technology that some perceive as threatening their job security, ethical safeguards are integral rather than incidental. Participation would be voluntary and preceded by an information statement describing the purpose of the study and the intended use of the data; no personally identifying information or employer identity would be collected; responses would be reported only in aggregate; and participants would be free to withdraw at any point before submission. Approval from the relevant institutional research ethics committee would be obtained before data collection begins. These provisions also serve a methodological purpose, since assurances of anonymity reduce the social-desirability pressure that self-assessed performance items are otherwise prone to attract.

Table 6: Proposed research design, procedures and quality criteria

Design element	Proposed procedure	Quality criterion
Population and sample	Generation Z employees in Bangkok using artificial intelligence at work for at least three months; unknown population	Screening items confirm cohort, location and experience
Sample size	Three hundred and eighty-five respondents, with a ten per cent reserve	Exceeds the regression minimum of Tabachnick and Fidell (2013)
Instrument	Three-part electronic questionnaire; twenty Likert items and one open item	Items adapted from established acceptance and appraisal scales
Content validity	Review by three qualified experts; item-objective congruence computed	Index of 0.50 or above retained; others reworded or removed
Reliability	Pilot test with thirty comparable respondents	Alpha coefficient of 0.70 or above per scale (Hair et al., 2010)
Analysis	Descriptive statistics; multiple linear regression by the enter method	Assumption checks for residuals and multicollinearity
Ethics	Voluntary, anonymous participation with institutional approval	Informed consent and aggregate reporting only

Source: Compiled by the authors from chapter three of the source proposal.

5. Discussion and Implications

The theoretical implication of the framework concerns the criterion variable. Acceptance research has customarily terminated at intention or self-reported use, on the reasonable assumption that use is what organisations pay for. Yet in the generative artificial intelligence setting, use is cheap and nearly universal among young employees, so that the interesting variance now lies further downstream, in whether use translates into better work. By placing employee performance, operationalised through the appraisal dimensions of Bernardin and Russell (1998), at the end of the chain, the framework converts the acceptance model from a theory of adoption into a theory of augmented productivity. It also brings the acceptance tradition into contact with the performance literature of Campbell et al. (1993) and Mathis and Jackson (2010), two bodies of work that have developed largely in parallel. A second theoretical contribution is the explicit cohort restriction: rather than treating generation as a control variable, the framework treats a single cohort as the unit of theorising, which is defensible given the evidence of Wei et al. (2025) and International Workplace Group (2025) that acceptance dynamics differ systematically by generation.

For managers and human resource practitioners, the framework carries three practical implications. First, if perceived usefulness proves to be the dominant predictor, as the weight of prior evidence suggests it may, then investment should favour demonstrating task-specific value over generic technical training; the determinants identified by Venkatesh and Davis (2000), particularly job relevance, output quality and result demonstrability, indicate how such demonstration might be organised. Second, the ease-of-use pathway implies that interface design, onboarding support and the reduction of extraneous cognitive load in the sense of Sweller (1988) remain worthwhile even for a cohort already fluent with digital tools, since the marginal effort saved is reinvested in wider application. Third, the attitude pathway directs attention to the affective conditions of adoption. Park et al. (2024) and Kelly et al. (2023) show that trust, transparency and the absence of job-insecurity anxiety are what sustain a positive evaluation, which implies that clear organisational statements about how artificial intelligence will and will not be used in staffing decisions are an adoption instrument in their own right, not merely a communication courtesy.

For the Thai context, the framework and the design proposed for testing it respond to a policy environment in which the diffusion of artificial intelligence is advancing faster than the evidence base that should guide it. The indicators compiled in Table 1 describe a workforce that is enthusiastic and a labour market in which artificial intelligence skills already carry hiring weight, yet the empirical basis for allocating training budgets across usefulness, ease of use and attitude remains thin. A predictive equation estimated on Bangkok employees would give human resource departments a defensible basis for such allocation and would allow public agencies, which face tighter procurement and training constraints than large private firms, to benchmark their own adoption programmes. More broadly, the design is deliberately replicable: the same instrument could be administered in provincial centres, in other cohorts, or in specific industries, so that the Bangkok study becomes the first point in a comparative series rather than an isolated result. Sukhumvit et al. (2025) illustrate the value of such context-specific Thai evidence, and Avaradi (2024) reminds us that the gap between technological capability and workforce readiness persists wherever training does not keep pace with the tools.

6. Conclusion

This paper has developed a conceptual framework extending the Technology Acceptance Model of Davis (1989) to the use of generative artificial intelligence by Generation Z employees in Bangkok, with job performance rather than usage intention as the criterion variable. It synthesised the definitional and dimensional literature for perceived usefulness, perceived ease of use, attitude toward using and employee performance; specified five observed variables for each construct; advanced three principal propositions linking each acceptance belief positively to performance, together with two auxiliary propositions reproducing the internal structure of the acceptance model; and set out a research design comprising a validated five-point Likert instrument, a target sample of Generation Z employees in Bangkok, and multiple linear regression leading to a predictive equation for performance.

The limitations of the paper follow from its conceptual character. No data have been collected and no relationship has been estimated, so every proposition remains a claim about what the literature leads one to expect rather than a finding. The framework is also deliberately parsimonious: it omits the moderators that recent work has found consequential, including the psychological safety, technostress and trust examined by Wei et al. (2025) and the anxiety and job-insecurity dimensions described by Park et al. (2024), and it treats the three acceptance beliefs as parallel predictors rather than modelling the mediated chain that Proposition 4 and Proposition 5 describe. The reliance on self-reported performance is a further constraint, since supervisory or objective indicators would provide a stronger test.

Future work should proceed in three directions. The immediate step is the empirical study for which this paper prepares the ground, testing the three propositions on a Bangkok sample and estimating the predictive equation. A second step would extend the model to the mediated structure implied by the auxiliary propositions, using structural equation modelling to examine whether attitude mediates the effect of the two beliefs on performance. A third would introduce the moderators and the negative attitudinal dimensions identified in recent literature, and would complement self-reported performance with supervisory ratings or archival indicators. Comparative replication across cohorts, provinces and industries would then establish how far a generation-specific acceptance model of artificial intelligence at work travels beyond the setting in which it was first specified.

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