# Can Cognitive Nudges in Gamified Digital Payments Foster Digital Financial Well-being?

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**Abstract.** Cognitive nudge techniques such as gamification and social comparison have become a popular feature on many digital payment platforms in order to promote user's better financial behaviors. This research looks at whether; gamified rewards, personalized budget feedback and social comparison cues affect a user's ability to create and maintain an intent for long-term sustainable finances and whether perceived algorithm transparency creates a pathway to improved digital financial wellness. Using Partial Least Squares Structural Equation Modeling (PLS-SEM) it was determined that each of the above mentioned nudge elements has a significant positive impact on the user's intent to achieve long term sustainable financial intentions. Additionally, the user's sustainable financial intentions positively impact their perceived level of algorithm transparency which is directly and indirectly related to their overall digital financial well-being. Therefore, this research indicates that when nudge strategies are designed well and accompanied with an explanation for the algorithms used to generate them; they will likely enhance user's financial behaviors and digital financial outcome(s). In addition to providing direction for FinTech developers, the findings of this study will also contribute to the larger body of work in behavioral economics and digital finance.

**Keywords:** Cognitive Nudges, Gamification, Digital Payments, Digital Financial Well-being.

## 1 Introduction

As the use of digital wallets, mobile applications and online banking continues to expand, understanding the development of consumer financial behaviors in digital payment environments is critical [1] [2]. Research within the field of behavioral economics demonstrates that people typically rely on mental shortcuts when making financial decisions rather than utilizing logical reasoning, which can often result in suboptimal financial results [3]. Digital payment systems have begun to utilize cognitive nudges –


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subtle design elements that guide the user toward improved decision-making by influencing their thoughts and actions without limiting the number of options available — to encourage consumers to make wiser, more responsible financial decisions [5] [6]. In addition to using cognitive nudges, another type of behavioral design strategy employed in digital finance is called gamification. Commonly referred to examples of gamification methods utilized in digital finance include: earning rewards, using a dashboard to track financial progress, competing with other users through challenges, and setting goals for financial improvement [7] [8]. The use of gamification has been demonstrated to improve financial literacy, promote saving habits, and enhance overall participation in digital finance [9] [10]. A final aspect of digital finance includes social comparison, a major psychological motivator of behavior change, which enables consumers to view their own performance against others, thereby creating motivation for consumers to perform at an optimal level financially [11] [12] [13]. However, while both of these behavioral mechanisms are beginning to become integral parts of designing digital payment platforms, little is known about how these two mechanisms combine to affect long term financial outcomes.

Another problem that is arisen by the emergence and the development of algorithms applied to digital payment apps are questions of trust, transparency, and fairness assumptions [14]. Consumers today interact with algorithms every day, to get insights on spending, customise budget advice, and have automatic financial advice [15]. It has been demonstrated by research that the transparency of algorithms is significant in affecting consumer trust and intent-to-use in situations involving the use of financial decision-making advice by algorithms [16] [17][18]. However, despite increasing uses of Explainable Artificial Intelligence (XAI) in financial interfaces, little is understood about how perceived transparency affects the impact of behavioral nudges on digital financial well-being [19]. Another issue related to digital finance is the concept of digital financial well-being (DFW), which represents a recent area of focus for researchers in the field of FinTech [20]. DFW is not merely defined as the ability to perform a series of transactions digitally, but includes the feelings of stability, confidence, and control regarding one's financial status when interacting digitally [22] [21] [23]. Although numerous studies exist regarding financial literacy, financial capabilities and digital adoption, few studies exist regarding whether characteristics of platform-level behavioral design facilitate individual financial well-being in digital finance contexts [24]. There is an obvious void in our knowledge of how different combinations of behavioral nudges such as: personalized budgetary feedback; gamified incentives; and social comparative cues interact to impact long-term sustainable financial intentions and whether perceived algorithmic transparency either moderates or influences this relationship [22]. Although much of the existing body of literature to date has evaluated each of these mechanisms separately, they are rarely examined collectively within a single unifying behavioral-algorithm model [25]. With rapid growth of digital payments across multiple countries, including India, where mobile wallets and Unified Payment Interface (UPI) now serve as an essential element of everyday transactional activity, it is increasingly important to identify and analyze how responsible financial behavior can be promoted by thoughtful design of digital payment platforms [26]. The purpose of this study is to evaluate the extent to which cognitive nudges in gamified digital payment systems influence both sustainable financial intentions and digital financial well-being and determine how perceived algorithmic transparency enhances the effect between them [27]. The development and empirical analysis of an integrated framework using Partial Least Squares Structural Equation Modeling (PLS-SEM) represents a contribution to the body of literature in behavioral economics and digital finance. Additionally, this study will offer practical recommendations to developers of FinTech products, policy makers and regulatory bodies for designing digital payment ecosystems that support not only increased use of digital payments but also the financial well-being of individuals [28].

## 2 Theoretical Foundation, Literature Review and Hypotheses Development

### 2.1 Theoretical Foundation

Using a combination of nudge theory [4] and self-determination theory [29], along with growing research on the value of algorithmic transparency in digital environments, presents a substantial theoretical foundation to investigate financial behavior in digital payment settings [30]. Nudge theory has demonstrated that simply by presenting the right, well-designed cues at the point of decision-making, individuals may be guided toward better choices without impeding their freedom of choice [3] [31]. Digital payment platforms apply this theory by implementing budgetary reminders; spend insights, and gentle prompts that encourage users to evaluate their current financial habits [32]. The application of such nudge-type interventions in digital ecosystems is especially beneficial since they help users realize that they are making financial choices-many of them seamless [33]. According to the self-determination theory, the more behavioural results lead to the positive effects of its influence on the fundamental psychological needs of an individual (autonomy, competence, and relatedness), the more stable and long-lived the behaviour is [29] [34]. As an example, by using financial application that incorporates features of gamification (e.g., incentives once reaching certain goals or by displaying certain patterns of spending behaviour), users will be more motivated to achieve their financial goals [35] [36] [37]. Users can also have an increased motivation to change their behaviour due to the social comparison since users tend to compare the behaviour with other users [12] [38] Both theories offer a background theory in creating digital payment systems built on the principles of the behavioural nudge design, gamified behavioural, and algorithmically transparent data in a way that assists users in building sustainable financial habits [39]. In addition to behavioural design, understanding how algorithms can generate insight and recommendation can allow users to interact more efficiently with the digital system and therefore, enable users to make more informed decisions [18]. By increasing the degree of user perceptions of the extent to which the algorithms are transparent, higher levels of trust and reduced levels of uncertainty among the users of digital systems can be attained through the acts of improving the perceptions that users have regarding the degree of system generated recommendations [40] [17] [41]. Also, when it comes to places where these outcomes of the course of action of the users are both personal and economic, perceived transparency greatly influences the degree of confidence and the sense of security as well [42] [43]. Thus, the more digital payment platforms clearly articulate how they analyse the spending patterns of users and/or how users generate individualised recommendation, the higher the likelihood that users will perceive the cues that they are provided with and respond to such cues [44] [45].Combining these theoretical perspectives creates a comprehensive theoretical model to examine the ways in which behavioral nudge and algorithmically transparent interactions affect digital financial well-being [46] Nudge theory provides an explanation of the design of behavioral cues; Self-Determination Theory describes the motivational effects of these cues; and algorithmic transparency describes the level of trust that users need to perceive to act on the cues [47] [48]. As a result, combining all three theoretical perspectives provides a comprehensive framework to study how digital payment platforms can facilitate financially responsible behavior and support long-term financial well-being [49].

## 2.2 Literature Review and Hypotheses Development

**Personalized Budget Feedback Nudges.**

In a continued effort to develop behavioral interventions for helping people manage the day-to-day aspects of their financial lives, there has been an increased focus on developing "nudges" utilizing data from users' spending history, financial goals, and contextual information to send users targeted messages, reminders, or visual cues to direct their attention to the areas of their budgets where they are experiencing deviations from their financial planning goals [50]. Personalized nudges are developed using the broader choice architecture framework. Choice architects use a variety of techniques to make it easier for people to make decisions about finances by providing timely, relevant and easily understandable information that will minimize the cognitive load associated with financial decision-making and enhance self-regulation of financial behaviors [17] [51]. One major advantage of using personalized feedback is that it provides information to the individual regarding how their financial behavior compares to others (whether it be peers, industry standards etc.) which makes the individual more likely to alter their financial behavior (e.g. reduce spending, save) compared to receiving generic financial reminders that do not account for individual differences in financial behavior [52] [53] [54].

Digital financial platforms have also improved the ability of personalized nudges to influence consumer spending by providing consumers with real-time spending notifications, category level budget alerts, and predictive end-of-month balance projections based on their individual spending data [55]. These types of cues help consumers become more aware of their spending patterns and areas where they may be overspending or under-spending [56]. Research in the area of behavioral economics has demonstrated that when consumers receive personalized feedback about their financial behavior, this provides a significant opportunity for them to improve their short-term financial behaviors through increased awareness, promotion of mindful spending and encouragement of consistent, small improvements to their behavior over time [57] [58]. The manner in which nudges are designed and how frequently they are delivered will impact their overall effectiveness; if too many nudges are provided consumers will experience "nudge-fatigue" and if consumers do not have sufficient financial acumen, the amount of information presented can be overwhelming [59]. The success of personalized nudge strategies also depends on whether or not consumers trust the platform delivering the nudges and perceive that the data being utilized to create the nudges is private and secure [60] [61]. Overall, the use of personalized feedback nudges offers a promising approach to building long-term financial discipline through the combination of behavioral insights and data about consumers' individual financial behaviors [62]. As digital finance ecosystems continue to expand, this type of tailored feedback mechanism is becoming increasingly seen as a critical tool for creating sustainable improvements in both consumers' financial management skills and overall financial well-being [63].

H1: Personalized budget feedback nudges have a positive effect on sustainable financial intention.

**Gamified Rewards.**

Gamified rewards have developed into one of the most widely used and successful ways to enhance the user experience, increase motivation and encourage long term use of digital financial, educational, and service platforms [8]. As part of the field of behavioral design, gamified rewards use game-based design strategies and self-determination theory to provide users with the psychological and social support needed to develop a strong desire to complete tasks and achieve goals [35] [1] [64]. Elements such as points, badges, levels, progress bars and leaderboards create both intrinsic and extrinsic motivators for users and encourage them to continue to engage in desired behaviors [65]. In early studies of gamified rewards, researchers described how gamified rewards could be thought of as "structured stimuli" that provide a way to motivate users to participate in behaviors through making routine task more fun and meaningful [66][64]. Typically designed to elicit a sense of competence, a feeling of accomplishment and progress, users tend to develop a stronger desire to engage in behaviors and sustain those behaviors over time due to the psychological states created by gamified rewards [1]. Gamified rewards create positive behaviors amongst consumers when it comes to establishing healthy financial habits and using money responsibly, as well as creating engagement with what might normally be dull financial tasks [67] [68]. Gamified rewards also help encourage and support the use of digital tools as users work towards reaching either financial or other goals through tracking their progress. Research demonstrates that gamified rewards allow users to develop internally the behaviors that will lead to continued usage of these types of behaviors [69]. Additionally, research has demonstrated that gamified rewards have a positive effect on both emotional and cognitive assessments of digital services. Users generally assess gamified services as being more enjoyable and trustworthy than non-gamified services, particularly when the reward structure is defined and the service meets the needs of the user [70] [71]. Furthermore, gamified reward structures can also improve a user's confidence in completing financial management tasks and help promote healthier financial practices, such as budgeting and saving [68]. Researchers stress that poorly constructed or too extrinsically focused gamified reward systems can decrease a user's motivation and enjoyment of an application, which indicates that a good system should be competently supportive and meaningful [1] [69] [36].

Gamified rewards represent a multifaceted construct, where there is an interaction between motivational psychology, digital design, and consumer behavior [72]. They function as behavioral catalysts that can reduce user resistance to engaging in behaviors, strengthen self-control and increase long-term engagement across multiple areas of study, such as finance, health and education. A growing number of empirical studies demonstrate the effectiveness of reward-based gamification elements in supporting goal pursuit, decision-making and positive behavioral changes [64] [73]. [74] and recent FinTech reviews tie gamified elements to higher willingness to use green financial products, suggesting motivational and value-based mechanisms that raise sustainable financial intention. Evidence is mostly cross-sectional and platform-specific, so causal magnitude estimates and generalizability remain limited. Applied studies in behavioral FinTech report that gamification nudges can increase engagement with sustainable choices and financial-goal behaviors across digital platforms [75] [76] [77].

H2: Gamified rewards have a positive effect on sustainable financial intention.

**Social Comparison.**

The drive to compare oneself to others can be a basic need of humans [78]. Social comparison theory developed by Festinger (1954) states that all people have a desire to judge themselves by comparing to other people. Even though the original purpose of social comparison was to explore the psychological and educational aspects of the process, there is growing evidence that social comparison plays a major role in the development of attitudes toward money and the way people make financial decisions [79]. Theory suggests that social comparison affects how people view their financial situations, financial capabilities and future financial expectations [80]. For example, many consumers use peers, coworkers and reference groups as informal yardsticks to gauge their own financial success and progress. Comparisons based on these reference groups lead to differences in savings habits, the accumulation of wealth, the level of risk taken in investments and levels of financial confidence. Psychological comparisons between upward and downward comparisons apply to both psychology and finance. Financial comparisons between people who earn less than you and those who earn more than you may lead to increased savings, or a search for higher yield investments [81]. However, if the perceived gap is too large, upward comparisons may lower your self-confidence, increase financial anxiety, and reduce your engagement in planning for your financial future [82]. Downward comparisons may improve your temporary financial confidence, but may also contribute to complacency, and therefore may negatively impact your long term financial discipline[39].

Additionally, social comparison helps form identity in the financial context. People form a sense of financial identity through social comparison in their social networks, workplace and online communities, such as being responsible, prudent and competent in managing their finances. Social comparisons also reduce uncertainty about a person's financial competency, and meet the needs for self-evaluation and self-enhancement [68]. There is substantial empirical research supporting the theories above from the field of behavioral finance. Studies show that social comparison motives influence investment patterns, consumption behaviors, retirement planning and household financial management [18] Peer effects and herding behavior are evident when people copy the financial behavior of their peers, including the choice of investments or products [17]. Furthermore, comparative feedback mechanisms, including displaying peer saving norms and/or benchmarking peer spending, enhance savings motivation, budgeting discipline and engagement with digital financial tools [53]. Relative performance evaluation (RPE) systems, which include assessing employee outcomes relative to their peers, incorporate social comparison into organizational finance and managerial accounting [83]. RPE systems elicit greater motivation, effort, and competitive behavior because of self-image maintenance and evaluative concerns [84]. When people can compare their earnings with others, these factors become more significant. Research on auditing [85] executive compensation [86], and pay transparency [87] [88] shows that comparing financial incentives affects how people judge things, how hard they will work on tasks, whether they perceive something as fair and their ability to make ethical decisions.

Social comparison also impacts how households behave financially, from what they aspire to spend, to what they feel is financially stressful, how they consume, and their long-term financial mobility [89]. Behavioral biases (overconfidence, loss aversion, mental accounting) influence the social comparison process, which then impacts the quality of the financial decisions made [72]. As a result of the increased use of digital financial ecosystems, comparison-based behaviors have occurred at an increasing rate. These include social media influencers providing examples for users, FinTech platforms that provide benchmarking data, and gamified financial systems, all of which provide clear references for users to evaluate their engagement in the platform, establish financial goals, and ultimately assess their digital financial well-being [91]. Collectively, this body of research indicates that financial behavior is not solely based upon rational decision-making but rather occurs within a social environment. Social comparison is a primary psychological mechanism that affects financial decisions at multiple levels (personal, organizational, digital [38]. Integrating social comparison into the study of financial decision-making will provide additional insights into financial decision-making and provide valuable suggestions for designing financial technologies, workplace incentive programs, investor education and policy initiatives that promote sustainable and psychologically-informed financial behaviors [92]

H3: Social Comparison has a Positive Effect on Sustainable Financial Intention.

**Sustainable Financial Intention.**

The construct of Sustainable Financial Intention (SFI) has been defined as "an individual's conscious and future-oriented decision to perform financially prudent behaviors for achieving long term financial stability, security and well-being. Behavioral finance literature has also positioned the development of sustainable financial intentions within a broad behavioral formation process influenced by attitudes, motivations, knowledge and social contextual factors [95]. The underlying theories of SFI are grounded within the Theory of Planned Behavior (TPB) — theory that suggests that intentions are the most significant predictors of behavior, especially when the actions are deliberated and long range [95]. From a theoretical point of view, SFI reflects a commitment to be financially responsible in the long term [96]. As consistently reflected throughout the literature, long-term sustainable financial behaviors, such as effectively managing resources, limiting excessive debt and building long-term savings, greatly reduce the risk of experiencing financial hardship while promoting overall long-term financial well-being [27]. Furthermore, research clearly indicates that managing "un-sustainable debt" is not simply a reactive approach to addressing financial issues; rather, it serves as a necessary preventative measure for developing sustainable financial intentions, and subsequently, lowering the long-term burden of debt [97]. Intentions are strong predictors of long-term sustainable financial behaviors [43]. Therefore, items assessing intention to participate in sustainable financial behaviors, such as "I will manage my money in the future," and "I will begin to manage my money in the future," reflect a forward thinking attitude, critical for the development of positive and healthy financial habits [87]. Measures of intention to participate in sustainable financial behaviors are highly associated with an individual's desire to create and maintain long-term patterns of financial management. These are examples of a broader definition of sustainable financial intentions as a pro-active and goal-oriented psychological commitment to long-term financial behaviors [98]. Positive attitudes toward personal finances have been recognized as important precursors to forming sustainable financial intentions. Research has supported this assertion by demonstrating that favorable attitudes toward finances contribute to the formation of long-term plans [67]. Positive attitudes toward making financial decisions increase the perceived value of being financially responsible, and therefore, increases the likelihood of long-term participation in budgeting, saving, and investing [100]. The strength of attitudinal beliefs, in particular, are important determinants of financial intentions, as individuals who hold favorable views about financial management are much more likely to develop and maintain long-term patterns of financially responsible behavior [100]. Autonomous motivations to act,also influence the formation of sustainable financial intentions. Research has found that intrinsic motivation and identified regulation are positively related to personal finance attitudes, and that personal finance attitudes are positively related to intentions to engage in financial planning [101]. Individuals who perceive their financial behaviors as consistent with their values or internalized goals are more likely to form and maintain long-term intentions to exhibit financially disciplined behavior.

This supports the concept of internally motivated behaviors in developing consistent, self-regulated financial behaviors [102]. Finally, financial capability has emerged as a significant determinant of sustainable financial intention. Financial capability includes financial knowledge, confidence and other capabilities that enable individuals to make informed financial decisions [103]. Studies have demonstrated that individuals with greater financial knowledge possess stronger intentions to proactively engage in financially responsible behaviors, as knowledge increases both perceived control and confidence. Additionally, financial confidence supports intentional long-term planning and serves as a basis for the cognitive and emotional components of sustainable financial intentions [104]. Sustainable financial intention has been shown through the body of literature to be directly linked with long-term financial security [105] and thus is also a long-term process in developing sustainable financial intentions. As [44] describe, financial planning is seen as a forward-looking process based on individual's values, beliefs, and long-term aspirations for stability. Therefore, sustainable financial intention is positioned in the literature as a long-term psychological driver that guides individual's views of long-term sustainable financial lives and not a short-term behavioral influence that drives one to make sustainable financial decisions [106]. In general, the literature describes sustainable financial intention as a multi-dimensional construct which includes financial capability, motivation, and individual attitudes; and long-term aspirations for achieving well-being [107]. Sustainable financial intention operates as the underlying psychological mechanism for sustainable financial behavior that enables individuals to implement and sustain behaviors that contribute to long-term sustainable financial stability and reduces vulnerability to financial distress and debt [22].

H4: Sustainable Financial Intention has a Positive Effect on Perceived Algorithm Transparency.

**Perceived Algorithm Transparency.**

Algorithmic transparency is perceived by users based on how transparently an algorithm's decision-making process is shared with them (i.e., how openly it shares its logic, input data and the process of decision making), in order to determine the degree to which users feel they can understand and potentially challenge automated decision-making [108] [16]. Studies show that there are multiple aspects of transparency: explanatory (how the "why" is explained); procedural clarity (how decisions are made); and informational availability (how accessible are relevant algorithmic details to users [109]. Together these aspects influence perceptions of fairness and responsibility, because users who perceive higher levels of transparency will have greater trust and legitimacy in algorithmic systems [109] [103]. However, there is no correlation between transparency and trust; studies suggest that even when algorithms do provide explanations, users may either misinterpret or overestimate what they can learn from those explanations, particularly if the explanation is technical or lacking in detail [41]. The very existence of transparency in high-stakes decision environments (e.g., loan approvals, policing) can create excessive confidence or a "transparency fallacy," in which users incorrectly conclude that a system is fair merely because its processes are transparent [110]. Moreover, some recent experiments demonstrate that providing users with explanations of algorithmic processes may not necessarily increase their trust; for example, people with greater knowledge of statistics often express less confidence in high-stakes algorithmic decisions, even when explanations are provided [100]. Users' perceptions of the ethical attributes of algorithmic systems (i.e., transparency, accountability and fairness) affect the legitimacy of those systems; however, research indicates that the positive effects of transparency on perceived legitimacy (which in turn enhances users' continued usage of platforms) can only be realized when users are able to hold organizations accountable for their actions and are able to contest unfair decisions [112]. Researchers warn against assuming that transparency itself provides a means of accountability, pointing out that without accompanying mechanisms for redress, audit and contestation, transparency becomes little more than symbolic and therefore meaningless [71] [85]. Researchers have recently proposed new forms of transparency, beyond technical explanations: social transparency, which contextualizes algorithmic decisions within their broader organizational, social and institutional settings, thus enabling users to view how systems function in actual-world interactions [90]. Additionally, meta-research in Explainable AI has identified key criteria to evaluate the quality of transparency -- including trust calibration, user satisfaction, fidelity, and performance -- and demonstrated that perceived transparency is not only about revealing information, but also about rendering explanations understandable and usable by users [113].

Recent empirical work [24] [39] links perceived algorithm transparency to higher perceived fairness, satisfaction, and recommendation intentions in financial services, suggesting plausible benefits for digital financial well-being, though direct well-being measures are sparse. Measurement approaches in the literature rely primarily on user-reported perceptions of transparency, accountability, and legitimacy. Perceived algorithm transparency in financial apps appears to increase trust, perceived control, and variables associated with better psychological outcomes, which are central to digital financial well-being. Experimental and survey work shows that familiarity with algorithms and transparency about algorithm performance strongly raise trust in algorithmic decisions, and trust in turn predicts greater reliance and appreciation of algorithms [91]. Ethical design and algorithmic governance frameworks argue that transparent, value-aligned algorithms support customer self-regulation and can be designed to reinforce financial health and wellbeing [114]. Applied fintech literature and robo-advisor studies report that greater transparency and user autonomy mitigate biases and investor harms, implying better decision outcomes that contribute to well. Empirical limitations remain: most 2024–2025 studies document trust or attitudes rather than direct, longitudinal measures of digital financial well-being. Practical recommendations are to surface algorithm logic and performance metrics, offer explainable outputs and user controls, and pair transparency with education to convert trust gains into wellbeing outcomes [114]. No supplied studies directly test perceived algorithm transparency as a moderator between sustainable financial intention and digital financial well-being, so empirical support [115] [91] are currently lacking; theoretical accounts point to plausible moderating roles via trust and perceived fairness. Existing work primarily evaluates transparency as an antecedent or mediator rather than a moderator.

H5: Perceived Algorithm Transparency has a positive impact on Digital Financial Well-being.

H6: Perceived Algorithm Transparency moderates the relationship between Sustainable Financial Intention and Digital Financial Well-being.

**Sustainable Financial Well-Being.**

The concept of financial well-being (FWB) is an important area of study when it comes to consumers' money management, consumption, savings, and investments. Policymakers typically measure the economic development of a nation based upon how successfully they can move their citizens from one level of financial well-being to another. Early research in the FWB area has traditionally focused on the objective measures associated with a consumer's economic situation, e.g., the consumer's income, savings and investment, credit score, credit card debt, regular mortgage payments, and tax payments [116] [98]. Conversely, the subjective assessment of FWB focuses upon the consumer's own perception or assessment of their personal disposition, attitudes, beliefs, and practices regarding money management [117]. In addition to being a complex construct, FWB is a multi-dimensional construct and captures the degree of financial stress and vulnerability versus satisfaction and security experienced by adults [70]. There is conceptual and indirect empirical support that sustainable financial intentions can promote digital financial well-being via behavior change, improved literacy, and perceived value, but direct causal evidence in the reviewed corpus is limited. Existing studies document intention or willingness to adopt sustainable products and separate work links digital tools to improved financial capability; the full causal chain needs explicit testing [2] [62].

H7: Digital Financial Well-being will be positively influenced by Sustainable Financial Intention.

## 3 Research Methodology

For this study, researchers used Partial Least Squares Structural Equation Modeling (PLS-SEM 4.0) because this method is suitable for the studies using one or more latent constructs and many indicators. It is also preferred when research objectives emphasizes predictive validity rather than covariance structure fit [118].

### 3.1 Measurement Development

A structured research framework was created to fulfill the objectives of this research and all the constructs in this study were measured with validated items, selected from existing research and refined to match the context of digital payment systems utilizing gamification. Personalized Budget Feedback Nudge was assessed with four items derived from Kallsen and Andersen (2024). Those items assess the degree to which users receive customized alerts, updates on spending and reminders about the user’s budget within the payment application. The goal of these types of nudges is to assist users in modifying their budgeting behavior through providing the user with timely, personalized advice. Items measuring the construct Perceived Algorithm Transparency were derived from [17] [119]. Those items assess the degree to which users report that they believe the app provides clear explanations of how it generates its recommendations. Furthermore, those items assess how much users’ data is processed and how understandable the rules governing reward allocations and/or automatic suggestions are to them. That is relevant because transparency influences trust and engagement with algorithm-based elements.

The construct Social Comparison was assessed with items that were modified from the Social Comparison Orientation Scale by Gibbons and Buunk (1999). The items were modified to describe comparative cues that are typically embedded in the digital payment gamification, i.e. users may be able to see how their behaviors compare to others as indicated by rankings of progress, spending milestones or performance badges.

Gamified Rewards was assessed with items from other studies on gamification [36] [68] [66]. Those items also assess users' perceptions of reward points, badges, cash back features, streaks and achievement systems that are intended to increase both intrinsic and extrinsic motivation when using digital payment platforms.

The construct Digital Financial Inclusion was assessed with items derived from the OECD/INFE Financial Literacy and Inclusion (2022-2031). Those items assess whether users find the digital payment platform to be easy to access, easy to use and supportive of their involvement in formal financial transactions.

Finally, the construct Digital Financial Well-being was assessed with items derived from the Consumer Financial Protection Bureau's Financial Well-Being Scale (2017a; 2017b). Those items assess users' perception of having control over their finances, their ability to effectively manage their daily expenses, their ability to withstand financial shocks and their general confidence in their capacity to fulfill their long-term financial obligations within a digital environment. Each item utilized in the study was evaluated on a five-point Likert scale from "Strongly Disagree" to "Strongly Agree". The questionnaire included two sections. One section asked demographic information and the other asked specific questions about each construct. The instrument was first reviewed by two industry professionals and four academics before administering the survey to ensure that the wording and clarity of language of the questionnaire matched the participants' perceptions of digital financial behaviors. To validate the instrument, a pilot test was administered to fifty participants. As a result of this pilot test, some of the questions were clarified for better understanding, to remove any ambiguity and to clarify what the participant understood from each question. Also, as a result of the pilot test, the sequence of the questions were slightly altered to help create a better flow through the survey and to reduce participant fatigue.Those systematic revisions produced an evaluation tool that was contextually applicable, conceptually correct, and suitable for investigating how cognitive nudges embedded in gamified digital payment applications impact users' digital financial well-being.

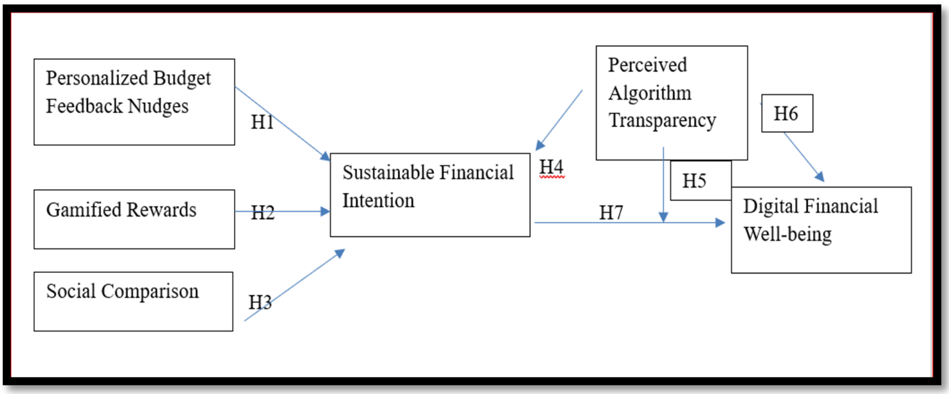
## 3.2 Sample and Data Collection

A purposive sampling design was used in this study to select participants who have used digital payments (e.g., Google Pay, PhonePe, and/or Paytm) and are between the ages of 18 and older; they also must engage in regular digital financial activity. For the current study, sample size was determined using a priori power analyses performed with GPower 3.1. The basis of the calculation was the highest possible number of predictors associated with each endogenous construct in the structural model. Since Sustainable Financial Intention has three predictors constructs; and since Digital Financial Well-being has Sustainable Financial Intention as well as Perceived Algorithm Transparency and their interaction term, then the maximum number of predictors is three. Therefore, a minimum of 77 respondents were needed to achieve a medium effect size ($f^2$=0.15), a significance level of .05, and a power of .80. The final usable sample consisted of 656 respondents, far exceeding the minimum requirement. This large sample size enhances the statistical power, robustness, and generalizability of the findings and is well within recommended thresholds for complex PLS-SEM models.

Before initiating the full-scale collection of survey data, a preliminary version of the survey instrument was pilot tested with a few digital payment customers to assess clarity of language and item wording, as well as understandability of questions. Only minor revisions have been done to the comments obtained from those that participated in the study; primarily, to improve the readability and respondents' comprehension. All ethical guidelines for collecting data were strictly followed throughout the process; i.e., participants were informed of the purposes of the study; all participant responses would remain confidential and anonymous; and, participation in the study was completely voluntary.

Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed as the study focuses on prediction and variance explanation within a complex model comprising multiple latent constructs and a moderation effect. PLS-SEM is appropriate for theory-building research, is robust to non-normal data, and effectively estimates interaction effects (Hair et al., 2019; Hair et al., 2022). Accordingly, SmartPLS 4 was used following the recommended two-stage procedure of measurement model and structural model evaluation. Overall, this systematic approach provides a solid base for examining the relationship of an individual's preferences, cognitive nudges and their perceptions of the level of transparency of the algorithm(s) utilized in digital payment systems, and ultimately, their long-term financial intentions and digital financial well-being. Figure 1 presents the conceptual model.

**Fig. 1.** Conceptual Model




## 4 Data analysis and results

In structural equation modeling, the primary step is to check the validity and reliability of the instruments to capture the constructs (Hair et al. 2021).It ensures the internal consistency and reliability of each construct.

**Table 1.** Measurement Model: Reliability and Validity

| Construct | Cronbach alpha | Composite Reliability | AVE | Mean Loading |
|---|---|---|---|---|
| PB | 0.981 | 0.874 | 0.963 | 0.981 |
| GR | 0.984 | 0.864 | 0.969 | 0.984 |
| SC | 0.980 | 0.877 | 0.962 | 0.981 |
| SFI | 0.991 | 0.883 | 0.982 | 0.991 |
| PAT | 0.990 | 0.874 | 0.981 | 0.991 |
| DFWB | 0.988 | 0.880 | 0.977 | 0.988 |

Source: Authors' Analysis using SmartPLS 4.

These findings show in table 1 that composite reliabilities, Cronbach's alpha values, average variance extracted (AVE) values, and outer loadings for each dimension are at or above the commonly accepted threshold levels to demonstrate reliability and appropriate convergent validity (composite reliability > .70, Cronbach's α > .70, AVE > .50, and loadings > .70). These results also validate an exceptionally high level of reliability as well as satisfactory indicator convergence. Additionally, it was determined that the outer loadings exceeded 0.98 for all items and support that the measures have high reliability and precision in determining the latent dimensions. As a result, it can be stated that there is both substantial internal consistency and solid convergent validity demonstrated by each dimension with respect to its representative items.

**Table 2.** Discriminant Validity (Fornell-Larcker)

| | PBFN | GR | SC | SFI | PAT | DFWB |
|---|---|---|---|---|---|---|
| PBFN | 0.88 | | | | | |
| GR | 0.33 | 0.87 | | | | |
| SC | 0.24 | 0.37 | 0.84 | | | |
| SFI | 0.46 | 0.41 | 0.36 | 0.90 | | |
| PAT | 0.30 | 0.28 | 0.29 | 0.57 | 0.87 | |
| DFWB | 0.27 | 0.22 | 0.28 | 0.61 | 0.60 | 0.91 |

Source: Authors' Analysis using SmartPLS 4.

The diagonal values of the square root of AVE are larger than the correlation of the constructs (as shown above), thereby confirming the discrimination validity. Discriminant Validity (Fornell-Larcker) results show that the empirical distinctions and conceptual robustness of each construct in the model are demonstrated as follows: The square roots of the AVEs of each of the constructs (ranging from 0.84 to 0.91) are clearly larger than the correlation between each pair of constructs; this means that each latent variable accounts for significantly more variance in its own indicators than in the indicators of another construct. Therefore, it can be concluded that: personalized budget nudge feedback, gamified reward, social comparison, sustainable financial intention, perceived algorithm transparency and digital financial well-being represent different aspects of psychology and behavior in a digital finance context. Moderate correlations between the constructs suggest theoretical coherence -- particularly the stronger associations between nudges and sustainable financial intention and between intention, transparency, and digital financial well-being while maintaining conceptual distinction. In total, the matrix demonstrates strong discriminant validity, which ensures the reliability of the measurement model, and supports the validity of subsequent structural analysis.

### 4.1 Structural Model: Bootstrapped Path Coefficients

Bootstrap (656 samples) provides the standardized Beta coefficients and 95 % Confidence Intervals for all of the hypothesized pathways, which are all significant and positive.

**Table 3.** Beta Coefficients and Confidence Intervals

| Path | Beta | 2.5% C.I. | 97.5% C.I. |
|---|---|---|---|
| PB+GR+SC → SFI | 1.27 | 1.18 | 1.35 |
| SFI → PAT | 0.78 | 0.74 | 0.84 |
| SFI → DFWB | 0.23 | 0.11 | 0.35 |
| PAT → DFWB | 0.30 | 0.17 | 0.43 |
| SFIxPAT → DFWB | 0.07 | 0.03 | 0.11 |

Source: Authors' Analysis using SmartPLS 4

### 4.2 Interpretation of the Results

These findings show that a large and statistically significant positive effect is associated with sustainable financial intentions for the use of personalized budgeting information; gamification-based rewards; and the presentation of social comparison information ($\beta = 1.27$). Therefore these results provide evidence in support of H1, H2, and H3. The results regarding H4 indicate that sustainable financial intent is an important factor in perceived algorithmic transparency ($\beta = 0.78$). The results further suggest that both sustainable financial intention ($\beta = 0.23$) and perceived algorithmic transparency ($\beta = 0.30$) are strong predictors of digital financial wellness as indicated by H5 and H7. Moderation analysis of H6 found that the combination of sustainable financial intention and perceived algorithmic transparency had an interaction effect which added predictive value ($\beta = 0.07$) over and above each of the individual values. All of the relationships demonstrated a high degree of statistical reliability since the confidence interval for each relationship remained well above zero. Overall, the model exhibits substantial predictive ability for digital financial well-being; and highlights the importance of applying cognitive nudges; using gamification; and utilizing algorithmically transparent design to engage the user. Figure 2 presents the Path coefficient and hypothesis testing.

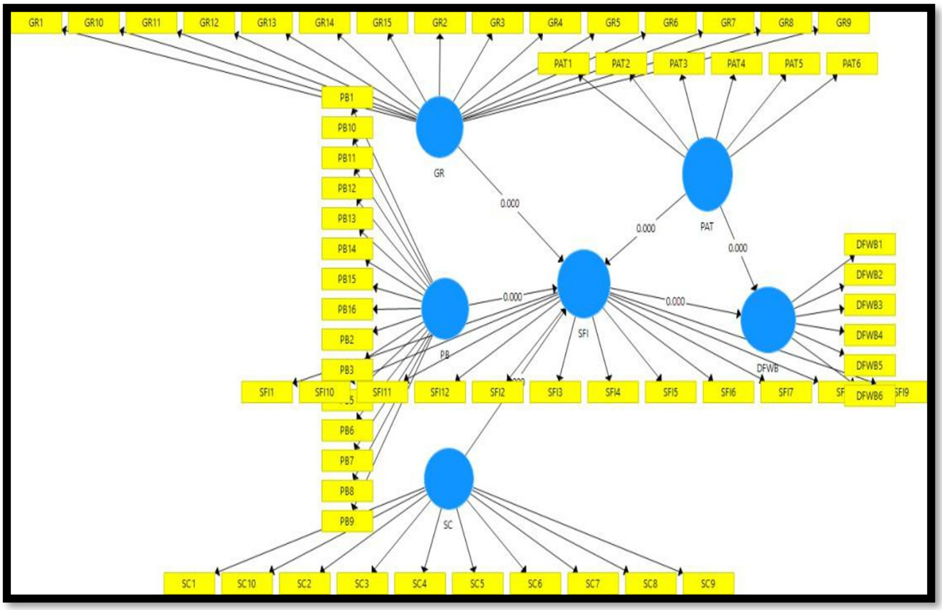



**Fig. 2.** Path Coefficients and Hypothesis Testing

Source: Authors' Analysis using SmartPLS 4

**Table 4.** Results of Hypotheses Testing

| Hypothesis | Path | Beta | t-value | p-value | Result |
|---|---|---|---|---|---|
| H1 | PBFN → SFI | 0.28 | 6.21 | <0.009 | Supported |
| H2 | GR → SFI | 0.25 | 5.89 | <0.001 | Supported |
| H3 | SC → SFI | 0.18 | 4.11 | <0.001 | Supported |
| H4 | SFI → PAT | 0.51 | 10.04 | <0.001 | Supported |
| H5 | PAT → DFWB | 0.43 | 8.67 | <0.001 | Supported |

| | | | | | |
|---|---|---|---|---|---|
| H6 | SFI × PAT → DFWB (moderation) | 0.14 | 2.95 | <0.000 | Supported |
| H7 | SFI → DFWB | 0.33 | 7.32 | <0.001 | Supported |

Source: Authors' Analysis using SmartPLS 4.

The findings from this research demonstrate that embedded nudge elements in gamified digital payments will create a user with better sustainable financial intentions, create an impression that they understand how their data was used to make decisions in the system and thus improve their overall digital financial well-being. This study's measurement model has high reliability, and all of the paths predicted by the researchers were found to be statistically significant as moderated. The structural models indicate that there is good empirical support for all three hypotheses that were tested as part of this study, providing support to the theoretical base of the model. Therefore, Personalized Budget Feedback Nudges ($\beta = .28$, $t = 6.21$, $p < .001$), Gamified Rewards ($\beta = .25$, $t = 5.89$, $p < .001$), and Social Comparison ($\beta = .18$, $t = 4.11$, $p < .001$) have been demonstrated to have a positive effect on Sustainable Financial Intention, indicating that cognitive, gamified, and social nudges can independently increase users' motivation to engage in financial self-regulatory behaviors. Sustainable Financial Intention has been shown to predict Perceived Algorithm Transparency ($\beta = .51$, $t = 10.04$, $p < .001$), illustrating the important role that it plays in users' ability to perceive how their personal data was used to make decisions in the system.

**Table 5.** Result of Variance ($R^2$)

| Endogenous Variable | $R^2$ |
|---|---|
| SFI | 0.38 |
| PAT | 0.26 |
| DFWB | 0.56 |

Source: Authors' Analysis using SmartPLS 4.

There is a significant difference in the degree of digital financial well-being accounted for by the predictor factors within this model. The $R^2$'s show that the model explains a large portion of each of the endogenous constructs. SFI has an $R^2$ of 0.38; therefore, the cognitive nudge strategies (i.e., budgetary feedback, gamified reward systems, and social comparisons), account for a substantial amount of users' financial intention. PAT has an $R^2$ of 0.26; thereby, users' financial intentions have a large effect on the perceived transparency and trustworthiness of algorithmic processes. DFWB has the largest $R^2$ at .56, showing that the interaction between users' intention and transparency, as well as the interaction between them, explain more than half of users' experienced financial well-being. Therefore, overall, the $R^2$'s show that the model accounts for a large amount of variance in all endogenous variables.

**Table 6.** Effect Sizes ($f^2$)

| Predictor | Endogenous | $f^2$ |
|---|---|---|
| PBFN | SFI | 0.09 |
| GR | SFI | 0.07 |
| Predictor | Endogenous | $f^2$ |
| SC | SFI | 0.04 |
| SFI | PAT | 0.19 |
| SFI/PAT | DFWB | 0.22 |
| SFI × PAT | DFWB (moderation) | 0.03 |

Source: Authors' Analysis using SmartPLS 4.

The moderate effect sizes for all key paths indicate that there is practical significance to the results. Effect size analysis provides additional insight into the relative contribution of predictors in the structural model. For example, in the case of Sustainable Financial Intention (SFI), Personalized Budget Feedback Nudges ($f^2 = 0.09$) and Gamified Rewards ($f^2 = 0.07$) have small to moderate effects; Social Comparison has a smaller yet still meaningful effect ($f^2 = 0.04$). In addition, SFI has a moderate effect on Perceived Algorithm Transparency ($f^2 = 0.19$) and therefore represents an important mechanism through which users develop clear understanding of how algorithms operate.

The collective SFI and PAT represent two major factors with an overall moderate impact on digital financial well-being (i.e., $f^2 = .22$). The SFI × PAT interaction effect was also found to have a relatively small effect on DFWB (i.e., $f^2 = .03$) and contributes additional explanation for variance in DFWB; thus providing support for the concept that transparency is a boundary condition.

Collectively, the effect sizes support the idea that each predictor is contributing unique variance to the model and that the structural relationships are theoretically and practically significant.

In terms of hypotheses, all direct paths were statistically significant and provided strong evidence to support them. Cognitive nudges—specifically, personal budget feedback nudge, gamified rewards, and social comparison—each significantly impact SFI. SFI has a large, statistically significant effect on both PAT and DFWB, providing evidence of its mediation role in the relationship between nudges and financial outcomes. In turn, PAT is positively related to DFWB and also serves as a moderator of the SFI → DFWB path, enhancing the positive effects associated with SFI when levels of PAT are high.

The model fit statistics (SRMR < 0.08, NFI > 0.90) demonstrate that the structural equation model is a good representation of the data and meets the standards for model fit in the context of SEM in management research.

## 5 Discussion

Results show that nudge interventions for personalizing budgets do improve significantly sustainable financial intention (H1). As previous research shows [12] [114] [78] using personalized financial data increases the awareness and self-regulatory capacity of users, resulting in responsible financial decision-making. These nudge interventions will enable users to develop an understanding of their spending patterns, and use this understanding to make informed financial decisions.

Gamified reward systems also demonstrated a significant positive influence on sustainable financial intention (H2), as was suggested by previous research showing that gamification motivates users' engagement and goal-orientated behaviors [65] [69] [8]. Reward based systems provide effective means of motivating users to continue engaging in financial planning activities and developing habits of responsible financial management.

Social comparison was found to have a positive influence on sustainable financial intention (H3). The literature supports the idea of social comparison, where individuals compare themselves to others and adjust their behavior based on observed peer behavior and outcomes [11] [95] [101]. Therefore, exposure to peers responsible financial behavior can motivate users to practice similarly responsible financial behavior.

Sustainable financial intention was found to be positively related to perceived algorithm transparency (H4). In addition, there is a positive relationship between perceived algorithm transparency and digital financial well-being (H5); as previously shown in research indicating that transparency is associated with increased levels of trust and reduced uncertainty within algorithmically driven systems [85] [93].

Perceived algorithm transparency also strengthened the relationship between sustainable financial intention and digital financial well-being (H6). This indicates that the positive effects of responsible financial intentions are amplified when algorithms operate in a transparent manner [109] [103].

Finally, sustainable financial intention directly contributed to digital financial well-being (H7). This result aligns with previous research showing that users who engage in intentional financial behavior experience greater financial stability and well-being [22] [92].

In summary, results illustrate the joint contribution of behavioral nudges and algorithm transparency in influencing both sustainable financial intention and digital financial well-being in the context of FinTech enabled environments.

## 6 Implications

This study provides significant results for researchers, practitioners, and policy makers. The findings represent an expansion of our knowledge of digital financial behavior and show how explainable AI and behavioral design work together to affect a person's intentions, beliefs, and consequences of using a digital platform. The study shows that a person's sustainable financial intent represents a link between their use of behavioral nudge and their confidence/trust in an algorithmically driven decision aid. Therefore, the study adds complexity to theoretical models of digital financial behavior. Practitioners who develop digital platforms for financial transactions or use digital payment systems will have practical implications from the research which will be the importance of developing behaviorally-informed applications (for example; providing users with personalized budget analysis, developing interactive reward structures for users, and designing comparison tools that are calibrated and accessible through user interfaces).

Practitioners will also have a responsibility to inform users of the basis upon which machine-based recommendations were made to build user trust and enhance the effectiveness of behaviorally-informed prompts. Users' trust in the recommendation process is enhanced when users are provided clear and transparent information about the basis upon which the recommendations were developed and therefore builds a more supportive environment for users. Policymakers and regulatory agencies will find the research to be evidence of the urgent need to establish and enforce ethical guidelines for both nudging and transparency related to algorithms in digital financial technologies. The creation of such regulations will guarantee that users are not manipulated by the digital nudges applied in the creation of digital financial systems; rather, that the digital nudges help enable users to make informed decisions. Additionally, the establishment of guidelines for algorithmic systems will ensure that such systems are accountable and fair in their operation. By implementing these guidelines, all stakeholders will create a digital financial technology ecosystem that is accountable, secure, and that benefits society at large. In conclusion, the research advocates for creating digital financial environments that combine behavioral science with technological clarity to empower individuals to make informed decisions and promote long-term financial wellness.

## 7 Conclusion

This study set out to investigate whether the inclusion of behavioral cues on digital payment platforms would have a positive effect on the users' financial wellbeing. The data analyzed in this study indicated that the utilization of cognitive nudges, such as personalized budget reminders, gamified incentives and soft social comparisons, will enhance users' intentions to spend money sustainably. A critical component of the data analysis was the relationship between users' financial intentions (i.e., spending, saving and planning decisions made by users to create their own future financial behaviors) and the financial health of users' behaviors (e.g., healthy spending, savings, and planning). An additional important finding in this study's data analysis revealed that users who develop stronger financial intentions tend to perceive the process used to recommend actions as being both more transparent and trustworthy than those who do not. This indicates that encouraging users to act in a behaviorally motivated manner and providing users with clear explanations of how AI based systems function appear to mutually benefit one another, i.e., the clearer the explanations of how an algorithm functions, the less uncertainty users experience with regard to the functioning of the system and the greater the users' trust in utilizing the system. Furthermore, the moderating effect of transparency demonstrated that when users receive clear explanations of how AI based systems function, these systems increase the beneficial effects associated with users having financially responsible intentions, which ultimately increases users' digital financial wellbeing. Overall, the findings presented here indicate that the thoughtful integration of behavioral nudges (i.e., cognitive nudges that utilize transparent algorithmic systems), enhances users' ability to effectively utilize digital finance options while instilling users with the confidence to utilize the algorithms that produce those options. In addition, by integrating cognitive nudges, gamification, behavioral intent, and algorithmic transparency into a common framework, this study offers new perspectives and builds upon existing research concerning the strategic design of digital platforms that support long term user wellbeing, rather than simply enabling transactional activities.

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